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Yanyan Li · Maiga Chang
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State-of-the-Art and Future Directions of Smart Learning

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Lecture Notes in Educational Technology

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Preface

The rapid development and popularization of information technology significantly increase the speed of the generation of human knowledge, which has brought fundamental impacts on the modes of education and the methods of instruction. The traditional ways of learning are facing a revolution to adapt to the requirements of the information age. In order to facilitate easy, engaging and effective learning for the learners, current digital learning environment is gradually evolving into the smart learning environment.

The International Conference on Smart Learning Environments (ICSLE) is a conference organized by the International Association on Smart Learning Environments. It aims to provide an archival forum for researchers, academics, practitioners, and industry professionals interested and/or engaged in the reform of the ways of teaching and learning through advancing current learning environments toward smart learning environments. It will facilitate opportunities for discussions and constructive dialogue among various stakeholders on the limitations of existing learning environments, need for reform, innovative uses of emerging pedagogical approaches and technologies, and sharing and promotion of best practices, leading to the evolution, design, and implementation of smart learning environments.

The focus of the contributions in this book is on the interplay of pedagogy, technology, and their fusion toward the advancement of smart learning environments. Various components of this interplay include but are not limited to:

- Pedagogy: learning paradigms, assessment paradigms, social factors, and policy
- Technology: emerging technologies, innovative uses of mature technologies, adoption, usability, standards, and emerging/new technological paradigms (open educational resources, cloud computing, etc.)
- Fusion of pedagogy and technology: transformation of curriculum, transformation of teaching behavior, transformation of administration, best practices of infusion, and piloting of new ideas.

ICSLE 2015 received 56 papers, with authors from 28 countries and six continents. All submissions were peer-reviewed in a double-blind review process by at least three Program Committee members. We are pleased to note that the quality of the submissions this year turned out to be very high. A total of 13 papers were accepted as full papers (yielding a 23 % acceptance rate). In addition, 14 papers were selected for presentation as short papers and another 12 as posters.

Furthermore, ICSLE 2015 features two distinguished keynote presentations and one invited presentation. Three workshops are also organized in conjunction with the main conference, with a total of 18 accepted papers.

We acknowledge the invaluable assistance of the Program Committee members, who provided timely and helpful reviews. We would also like to thank the entire Organizing Committee for their efforts and time spent to ensure the success of the conference. And last but not least, we would like to thank all the authors for their contribution in maintaining a high-quality conference.

With all the effort that has gone into the process, by authors and reviewers, we are confident that this year's ICSLE proceedings will immediately earn a place as an indispensable overview of the state of the art and will have significant archival value in the longer term.

July 2015

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Contents

Chapter 1
Influencing Metacognition in a Traditional Classroom Environment Through Learning Analytics

Wayne J. Brown and Kinshuk

Abstract Metacognition plays an important role in the learning process as it allows learners to become better aware of their level of understanding and comprehension. Knowledge of learners' metacognition level allows teachers to provide feedback to learners to enable correction of learning strategies. However, measuring metacognition based upon learner activities outside a computer-based learning environment is a challenging task. This paper explores this challenge in adult learners for the purpose of developing a learning analytics model that can be used to influence the use of metacognitive strategies to improve learning and comprehension. As a solution, a novel learning analytics model is presented. This model is based upon data captured from a traditional physical classroom environment and can be used to build a working learning analytics model designed to provide feedback to the learner. Such feedback can provide insights of learners' use of metacognitive strategies with a view to improving their comprehension of a given topic and thus to improve their understanding of that topic and ultimately to improve their academic success.

Keywords Metacognition · Self-directed learning · Learning analytics · E-learning · Learning and comprehension · Learning awareness

1.1 Introduction

One of the many challenges facing both college and university faculty alike is assisting learners in becoming more aware of their level of comprehension of course content and to use this awareness in real time to alter their study strategies to

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improve their academic success. The purpose of this research is to develop a learning analytics model that can be leveraged by future researchers to explore how data captured in the context of a traditional physical classroom environment can be used to influence metacognition in the adult learner. The model presented can potentially be used to influence the use of metacognitive strategies by adult learners, resulting in improved understanding of a given topic and potentially achieving higher grades. Although young children can be taught memory and cognitive strategies, they are unlikely to use these strategies spontaneously as this is a complex metacognitive act which is developed over time through experience, practice and support [7]. Consequently, the focus of this research is on adult learners as they have developed the ability to make conscious use of metacognitive strategies.

Capturing data within the context of a traditional physical classroom is an atypical approach to learning analytics in today's online learning and mobile computing environment. Much research has been conducted in building learning analytics models from data captured within the context of a computer-based learning environment (CBLE). A CBLE lends itself to the collection of data relative to learner activity as long as all learner activities take place within the CBLE. However, the purpose of this paper is to explore the practicality of capturing learner activity from a traditional physical classroom environment and in turn use these data to provide feedback to the learner for the purpose of influencing the use of metacognitive strategies to improve learning and academic success.

Monitoring learning behaviors has the potential to contribute to academic success for post-secondary learners [8]. The overall goal of this paper is to inform future research in the area of metacognitive processes in the context of the traditional physical classroom environment, thus enabling adult learners to more effectively practice metacognitive strategies to improve their overall understanding of a given subject and potentially improving grades.

The main research problem explored in this paper is as follows:

What parameters should be used to build a learning analytics model for a traditional physical classroom environment that could be used to influence the use of metacognitive strategies by adult learners?

The desired result of using metacognitive strategies is to enable adult learners to become more aware of their degree of comprehension of a given topic so they will take the necessary action to adequately prepare themselves for future assessments and thus improving their overall academic success.

Mytkowicz [8] has shown that many new college learners struggle because their past academic experiences do not sufficiently prepare them to handle the demands of college because their available learning strategies, and indeed their ability to select and apply the appropriate strategies, are poor.

Given its importance to post-secondary success, it is clear that metacognition should be taught explicitly to college and university learners [8]. The focus of this essay is inspired by a scenario that we witness often as post-secondary educators. The scenario to which we are referring is that ever-recurring situation in which a learner fails to comprehend their lack of understanding of a particular concept and proceeds to enter into a testing situation convinced of their superior grasp of the topic—only to receive a failing grade. After receiving the grade, the learner is surprised—even dumbfounded, and draws every conclusion as to the source of their failure, except that they truly do not understand the topic. The authors have observed that students with an advanced awareness of their own level of comprehension will take corrective action while studying to reference alternate sources of information to get a better understanding of a topic they are struggling with. So the question this scenario raises is as follows: Why is it that some learners are more aware of their own lack of comprehension then others?

1.2 Literature Survey

There is little evidence in the literature for building a learning analytics model from data captured from a traditional physical classroom environment. At the same time, much work has been done to capture data through direct interaction with the learner in an effort to gain a deeper understanding of metacognition and the use of metacognitive strategies. Common off-line techniques currently being used to capture these data are self-report questionnaires, interviews, and teacher ratings [9]. A common method for gaining insights into the process of task execution is the use of think-aloud techniques [10]. Researchers have been using these techniques for quite some time to better understand learners' metacognitive activities by asking the learners to 'think aloud' as they study or solve a particular problem. This technique is typically (if not always) conducted in a face-to-face context and serves to provide insights specifically into metacognition relative to the task a learner has been working through.

Self-report questionnaires on the other hand are developed with the aim of assessing metacognition using Likert scale questions. Generally, two types of questionnaires are used in metacognition research: general and domain specific. General metacognitive questionnaires are designed to assess metacognition independent of any specific learning domain or activity. Domain-specific questionnaires are designed to assess metacognitive activities in the context of a single domain or learning activity [10].

Another off-line technique to assess metacognition is simply interviewing the learners either shortly after a learning activity or in general. Mainly, there are three varieties of interviews used in metacognitive research. One interview approach is to simply ask the learners to describe their typical learning behavior or activities as they reflect upon past learning experiences. Alternatively, individuals are asked to describe their metacognitive behaviors after completing a specific task. In more advanced interview protocols, hypothetical learning situations are presented and learners are asked what strategies they could use in those particular situations [10].

Teacher ratings are another off-line technique of assessing the use of metacognitive strategies of learners. Teachers are requested to evaluate their learners' use of metacognitive strategies using an appropriate rating scale [9].

All of the above-mentioned techniques are focused on capturing data directly from learners using a human operator. Indeed the traditional approach to measuring learners' SRL-oriented thinking has been through self-report questionnaires. The questions are designed to assess various aspects of the learners' self-regulated learning strategies.

Online learning is the ideal scenario where this type of data can be captured, especially if learners are provided with an online learning environment within which all of their course work is completed. To improve learning from instruction, researchers, instructors, and learners alike need data that will give insights to the effectiveness of how a course is designed.

Winnie et al. [12] provides a good overview of software that is currently available to capture and analyze data from a learning environment. Software developed by the learning kit project is one example of the use of technology and computer-based learning environments to analyze and interpret data from an online learning environment. The learning kit provides scaffolds for learners to develop expertise in study tactics and learning strategies that align with aspects of instructional design theory. With trace data, the learning kit can reconstruct a complete time-referenced description of the learners' learning actions which give indication of how the learner studied. gStudy is another software solution that provides learning tools that learners can use to engage with multimedia information through indexing, annotating, analyzing, classifying, organizing, evaluating, cross-referencing, and searching learning content. Such tools for studying multimedia information are designed based upon research into ways to positively influence solo and collaborative learning and problem solving.

As described by [11], a more recent approach to learning analytics and the need to capture data from disparate inputs is the Tin Can API. This API is an emerging specification for learning technology that makes it possible to collect online and off-line learner experience data. Data are collected in a consistent format via assorted technologies and stored in a learning record store (LRS). Learner experiences are recorded in the form of secure 'noun, verb, object' statements (e.g., Bill attended lecture three on Pythagorean theorem) that are sent to the LRS. Once stored, these statements can be shared with other LRSs, LMSs, and reporting and analytic tools. Essentially, Tin Can allows the user to fashion a complete picture of an individual's learning journey based upon their experiences along the way. Most importantly, Tin Can is designed to record learning events in a personal data locker that becomes the property of the learner versus the University, the employer or the LMS. The aggregation of these learning experiences can assist researchers to identify the training paths that lead to the most successful outcomes as well as the least successful outcomes resulting in an overall measure of the effectiveness of a given training program.

Although not all learners successfully self-regulate, it is something that can be developed and learned over time [5]. Metacognition, a facet of self-regulated learning, is a complex, multifaceted structure that cannot be accurately assessed using a single technique or tool [9]. Both off-line and online techniques are required to provide accurate insight into metacognitive processes. Studies show that there is compliance between the teachers' opinions and the learners' opinions of themselves relative to their comprehension of a given subject [9].

1.3 Methodology

A literature review was conducted based upon peer-reviewed papers that were primarily published since 2010. The identification of appropriate papers was based upon a search for topics, including but not limited to, metacognition, learning analytics, self-regulated learning, metacognitive strategies, metacognitive awareness inventory (MAI), and online learning technologies. Papers were selected that described specific theories, research results, and background information relative to using learning analytics data to influence metacognition. Fifty-three papers and conference proceedings published primarily between 2010 and 2014, and relevant Web-based material, were selected and reviewed for this paper. Each paper was carefully reviewed to identify relevant material that would inform this study and the resulting proposed learning analytics model.

1.4 Issues, Challenges, and Trends

Research into theories of education seeks to identify causes of learning performance and the lack thereof. By discovering and understanding such causes, we are able to design appropriate interventions to improve learner comprehension and thus academic performance. However, research in this area is challenging due to the difficulty in measuring unobtrusively the metacognitive strategies employed by the learner [1]. Secondly, the literature provides little guidance on how to capture and interpret data about learner context in researching self-regulated learning [5].

Additionally, current self-report protocols reveal very little about how learners select and utilize specific learning tactics to form an efficient metacognitive strategy [5]. There is a need for greater insight into self-regulated learning by capturing more granular data that accurately reflects the learning journey and the learners' environmental variables, such as motivations and distractions.

When it comes to self-report surveys and interviews, results may not accurately reflect the learners' actions, as these tools capture results after the fact which may be subject to memory decay [5]. From a technical point of view, the accuracy of data collected from any of the above-mentioned tools remains the biggest challenge for data analytics. In this context, data collected is assumed to be free of bias from context and therefore should provide a true representation of the learning activities recorded [4]. However, in most learning settings, learners introduce contaminants into the dataset, usually unknowingly; indeed, this is a reflection of the complexity of metacognition. However, it is clear that if learners receive feedback on their performance, they may modify their self-assessments to be a more accurate reflection of their actual knowledge levels; thereby, the correlation between self-assessments and actual performance will increase [10].

With regard to the use of self-reports, reliability may be an issue, as participants may not always provide truthful responses or may provide responses that they feel the researcher is anticipating [6]. Alternatively, if the learners lack an appropriate level of self-awareness, they may report information which they feel is truly a reflection of their learning approach or level of comprehension yet is not at all accurate. This of course is a circular argument, as the very purpose of employing self-report methodologies is to ascertain the learners' metacognitive strategies which include self-awareness!

The MAI is a frequently used tool for data collection. Despite being used in several studies, the models and results generated from MAI scores are not conclusive [6]. Additionally, evidence suggests that the use of metacognitive skills is related in some way to the learners' intellectual ability; for example, strategies differ between average learners and gifted learners.

1.5 The Learning Analytics Model

The proposed learning analytics model (Fig. 1.1) is based upon the capture of data within the context of a traditional physical classroom environment (vs. a computer-based learning environment) and feeding the results of this data to the learners to provide them with insight into their use of metacognitive strategies and in particular their ability to predict their own learning outcomes by monitoring their own level of comprehension. The overall goal of the model is to provide the learners with the appropriate level of feedback so that they will take necessary actions to improve their level of comprehension, thus improving their academic success. The biggest challenge of the model is to understand how best to intervene to assist learners based on sound models of causal relationships [1].

One of the main goals of integrating traditional teaching methods with learning analytics is to improve teaching and learning quality [2]. Ultimately, what we wish to solve is the problem of learners walking into an assessment convinced that their degree of understanding of the subject matter is at an acceptable level, only to find out from the assessment results that they indeed have a very limited understanding of the subject matter. Hence, we are trying to equip learners with knowledge of their comprehension so that they can make better decisions regarding study strategies by improving their ability to monitor their own comprehension. To learn intentionally, learners must consciously understand and be able to identify their strengths and weaknesses, their unique learning strategies, the techniques they use to evaluate the way they execute learning tasks, how they monitor their own learning, and whether they are creating new ways to learn intentionally [6].

The question now becomes what data do we capture, how do we capture these data, and how do we present these data to the learners to motivate them to take affirmative action to better understand the subject matter and to improve their overall

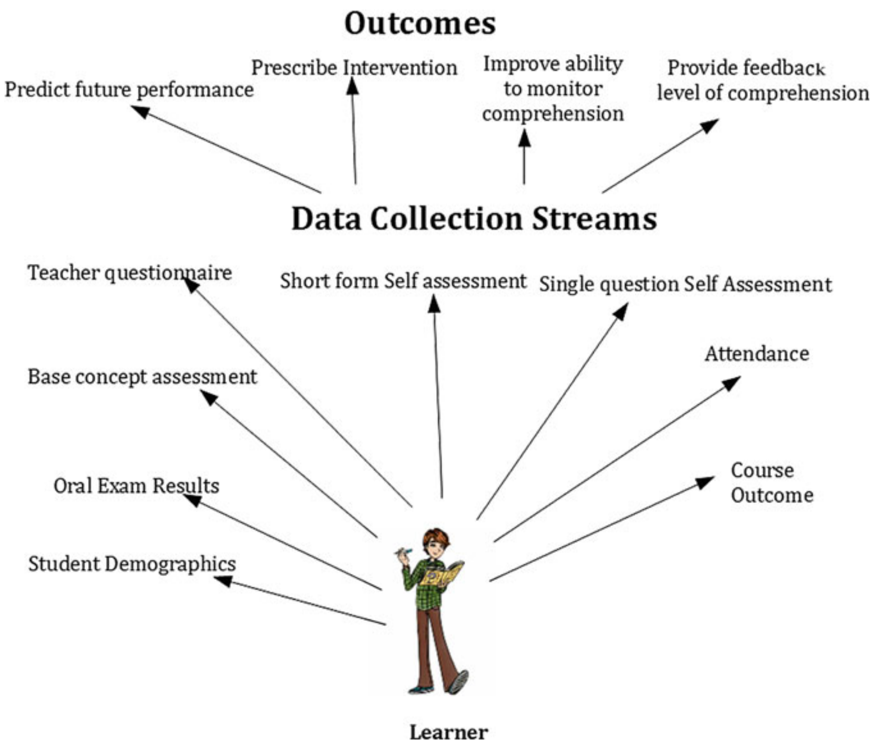

Fig. 1.1 Data analytics model

ability to monitor their own comprehension. Essentially, we are trying to develop or equip learners to become intentional learners. This development of intentionality requires educators to create learning opportunities to cognitively challenge their learners as well as to present the learners with tasks which will cause them to reflect upon their own learning process [6]. Integration of multiple and diverse data sources, both off-line and online, may lead to more pedagogically meaningful learning indicators because a more holistic picture of the learner is provided by the data [2].

The data capture streams proposed by this solution are as follows:

- teacher questionnaires;
- short three-question self-assessments at the beginning of each formal assessment;
- short one-question assessment at the beginning of each topic;
- multiple-choice questions on fundamental concepts that are grouped by concept;
- course outcomes measured against learner achievement;
- attendance; and
- oral exam results.

Teacher Questionnaire: The purpose of the teacher questionnaire is for teachers to provide their views about learners' ability to use metacognitive strategies and in particular provide commentary on the learners' ability to monitor their own comprehension of specific subject matter.

Short three-question self-assessment at the beginning of each formal assessment: This assessment is a direct 'measure' of the learners' views about their own overall comprehension of the material being presented in the assessment. Three simple questions placed at the beginning of each formal assessment ask the learners to rate their overall comprehension of the material and the strategies they used to prepare for the assessment.

Short one-question assessment at the beginning of each assessment topic: This assessment is a direct and more granular 'measure' of the learners' views about their comprehension of the specific topic being evaluated; this, for example, may be one question on an exam.

Multiple-choice questions on fundamental concepts that are grouped by concept: This is an assessment written specifically to evaluate the understanding of base concepts that when put together make up the pieces required to solve problems a given situation. There would be several multiple-choice questions on each concept that would be grouped together. From this evaluation, the learner would be able to quickly identify fundamental concepts that they do not understand and therefore may be impeding them in their ability to solve high-level problems based upon these fundamental concepts.

Course outcomes measured against learner achievement: This feedback would be based upon progress against published course outcomes as evaluated by standard assessment tools.

Attendance: Attendance is typically a fair predictor of a learner's probability of being successful in a course. These data would represent attendance in both lectures and laboratories where applicable.

Oral exam results: The instructor would draft a set of questions to probe the learners' understanding of base concepts of the course through an oral exam. Prior to the oral exam, the learners would be asked to rate their comprehension of each of the topics in which they will be questioned.

1.6 Learner Feedback

Once the data are collected and analyzed, it would be used to provide feedback to the learners to increase their level of awareness of their true comprehension of specific topics, provide a prediction of future performance, prescribe possible strategies that the learners can implement to improve their performance, and ideally help the learners to improve their ability to monitor their own comprehension.

Feedback is an important aspect of self-regulated learning in that it allows learners to compare their own views about their comprehension of a topic to their level of comprehension as evaluated by the feedback provided [3]. The reduction or elimination of this overconfidence will allow the learners to arrive at a more realistic judgment of their level of comprehension. The model presented utilizes three data streams to provide the learners feedback on their comprehension as measured by the model. These three data streams are as follows: short three-question assessment at the beginning of each formal assessment, short one-question assessment at the beginning of each assessment topic, and course outcomes measured against learner achievement. A formal review of the data from these three sources by the course instructor will provide the learners with valuable feedback that will provide insights to their own view of their comprehension of the material that is the subject of the review.

Consistent feedback sessions as described above will assist learners to improve their ability to monitor their own comprehension over time by becoming more intentional about their own learning. Intentional learners tend to understand their own self-capacity, their own learning processes, and examine the way they evaluate, monitor, and execute their own learning processes and comprehension [6].

Primarily, the teacher questionnaire data combined with the multiple-choice questions on fundamental concepts that are grouped by concept will equip the course instructors to prescribe to the learners study strategies that will assist them in becoming more self-directed and intentional learners. In particular, the multiple-choice questions on fundamental concepts that are grouped by concept will allow the instructors to pinpoint exactly what basic concepts the learners are struggling with relative to the assessment topic as a whole. This will allow the instructors to prescribe remedial work that builds the learners' understanding of these fundamental concepts so they are better equipped to tackle more advanced topics that are built upon these fundamental concepts. The other data streams (short three-question assessments, one-question assessments, course outcomes) will also provide insights into the learners' ability to monitor their own comprehension and thus discover strategies to provide feedback prior to a formal assessment.

Finally, the attendance data stream along with the course outcomes will allow the instructors to predict the future performance of the learners by identifying an academic success pattern that will continue unless evasive action is taken by the learner. The other data streams (short three-question assessments, one-question assessments) will also inform this discussion as a learners' ability to monitor their own comprehension will significantly inform their academic success.

From the above discussion, it can be seen that the course instructors play a significant role in helping the learners interpret the feedback provided by the model and to apply that feedback to alter their study strategies. The overall goal of the model is to train learners to interpret their own feedback so they can, without guidance, alter their study strategies when necessary.

Research suggests that self-assessments are strongly related to actual knowledge levels when learners are given opportunity to self-assess and receive feedback on their self-assessments [10]. However, Efklides [3] argues that judgments of learning can be flawed if the learners rely upon the inference that a certain topic may be more important than another because it is processed more fluently, or faster, yet in reality it is already well understood. In this case, the learner may be focusing their attention on material they have already mastered versus material they still do not understand. Additionally, basic psychological research suggests that the correlation between self-assessed knowledge and test performance may be low because some learners may simply be inaccurate in their self-assessments [10]. However, metacognitive judgments can be improved and monitoring can become more accurate if:

- the learners have prior knowledge that allows for evaluation of the correctness of their judgments;
- the learners are given corrective feedback; and
- the learners have understanding of how memory works and the factors that influence memory [3].

Recognition of prior learning strategy posits that learners monitor their improvement in learning as they study and therefore are able to conclude when they no longer need to study a topic they have mastered or stop studying altogether because learning abates when little progress is being made [3]. However, unintentional learners are influenced by external factors such as prior knowledge, types of tasks, and facilitation and thus will change their learning process accordingly [6].

This model may be most suited for those learners who struggle with math or other science concepts. Equipping learners to monitor their own comprehension is a significant step toward course success. Course instructors could design the questions for each assessment as well as the oral exam to gain insights into the learners' level of comprehension and use of metacognitive strategies. An exam on TCP protocol, for example, could be broken down into several fundamental concepts to build the multiple-choice questions that are grouped by concept; which will provide both the instructors and the learners insights of what fundamental concepts are not clearly understood. Technology courses in particular are conducive to this model. Feedback from the model can equip instructors to give learners feedback of what specific concepts the learners are struggling with and what resources and strategies the learners could use to improve their understanding of the course material.

1.7 Conclusion and Future Research

Learning analytics is still in its infancy and is seen by many as one of the technological advances that will bring learning to the next level [6]. However, there is still much work to be done to replace the insights gained by a human instructor when it comes to evaluating learner motivation and distractions. One of the challenges of learning analytics is its current reliance on computer-based learning environments. With this focus, there is a risk that the traditional classroom learning paradigm will not benefit from the research that is being carried out in the area of learning analytics. Interestingly, Lee [6] argues that there is a dark side to learning analytics. This view sees learning analytics as a mechanism for higher education institutions, governments, and private companies to use these data to manipulate the learners to paths they may not have chosen on their own [6]. Therefore, it is important that learning analytic models be designed from the learners' perspective to ensure that the interests of the learners are the primary motivator for design decisions and data usage [4]. Future studies should explore the relationships between intentional knowing and abilities such as problem solving and critical thinking which are important attributes of today's learners [6]. Additionally, further research should be conducted on the role of self-assessments and the potential benefits of administering self-assessments throughout a course with a view to understanding how quickly these improve in accuracy and how they influence learning processes [10].

There are indeed limitations to the work presented in this paper. Limited research has been conducted in the area of building learning analytics models based upon a traditional classroom environment; hence, the model presented here is based primarily on anecdotal evidence. Secondly, this model is written based upon a technical curriculum; therefore, the model may not be as effective if applied to non-technical courses.

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Chapter 2
Predicting Newcomer Integration in Online Knowledge Communities by Automated Dialog Analysis

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Abstract Using online knowledge communities (OKCs) from the Internet as informal learning environments poses the question how likely these communities will be to integrate learners as new members. Such prediction is the purpose of the current study. Based on the approaches of voices interanimation and polyphony, a natural language processing tool was employed for dialog analysis in integrative versus non-integrative blog-based OKCs. Four dialog dimensions were identified: participants' long-term persistence in the discourse, the community response to their participation, their communicative centrality, and their communicative peripherality. Hierarchical clusters built upon these dimensions reflect socio-cognitive structures including central, regular, and peripheral OKC members. While the socio-cognitive structures did not make a significant difference, integrative OKCs display significantly stronger peripherality, community response, and centrality as compared to non-integrative OKCs.

Keywords Knowledge communities · Newcomer integration · Dialog analysis · Social learning analytics

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2.1 Introduction

Online knowledge communities (OKCs) are frequently regarded in educational research and practice as collaborative environments for informal learning [1, 2]. OKCs display multilayered socio-cognitive structures that comprise central, active/regular, and peripheral participation. Central participants assume more responsibility and perform more difficult tasks than peripheral members; therefore, their identity is that of an expert. After a few decades of mainly qualitative research on communities, researchers are beginning to apply quantitative methods, including the identification of socio-cognitive structures, as shown by Nistor et al. [3], who validated an automated dialog analysis tool, ReaderBench [4]. The automated assessment of OKCs is based on the idea that community discourse is tightly connected with socio-cognitive structures, practice, and learning [2]. Further on, the ReaderBench tool is based on Bakhtin's dialogism [5] and on the polyphonic model of discourse [6]. ReaderBench provides several indicators describing the personal and social dimensions of a collaborative dialog, emphasizing dialog coherence and overall coverage of a given topic. These dimensions are strongly correlated with participants' expertise and critical thinking expressed in online, text-based discussions [3].

Using existing OKCs from the Internet for informal learning poses the question *how likely these communities will be to integrate learners as new, legitimate peripheral members* [2]. The present study aims to answer this research question, thus contributing to understanding and predicting this phenomenon, which will further provide a tool and method to make OKCs "smart" [1, 7].

2.2 Methodology

The study explores the socio-cognitive structures of OKCs that were likely versus unlikely to integrate newcomers (in the following called integrative vs. non-integrative OKCs), following three steps: (1) analyze the community discourse using the ReaderBench tool [3, 4]; (2) cluster the community members based on the resulting discourse characteristics; and (3) compare the clustering results in integrative versus non-integrative virtual communities.

The analysis was conducted on the Internet, in blogger communities publicly available on the blogspot.com and wordpress.com platforms. In a prior study, the researchers had posted a request for survey participation in several blog communities. Two situations emerged: one in which the blog participants responded to the request, and another in which the request was ignored or blocked. Consequently, it was assumed that the former group consisted of integrative (n = 10), the latter of non-integrative (n = 12) OKCs. After these N = 22 blogger communities with a total of 8122 participants were chosen for analysis, the community discourse produced during the entire lifetime of each OKC was downloaded and automatically analyzed. No personal data of the participants were collected.

The ReaderBench tool provides 13 dialog indicators: two overall indicators (number of comments, total collaborative dialog quality), one indicator of the individual contribution to the dialog (individual collaborative dialog quality), five indicators of the social contribution to the dialog (number of initiated discussion threads, length of initiated threads, cumulative interanimation of voices, social collaborative dialog quality, social collaborative dialog quality in initiated threads), and five centrality indicators in the sense of social network analysis (Indegree, Outdegree, Closeness, Eccentricity, and Betweenness).

2.3 Findings

Discourse Analysis. The absolute values of the variables ranged in large limits; hence, they were standardized. Further on, they were strongly correlated with each other; therefore, a principal component analysis was performed. Thus, the number of components was reduced to four factors with eigenvalues greater than 1, which explained 86.16 % of the total variance. The four dimensions resulting after oblimin rotation are based on different sets of the initial variables, as follows. Factor 1R is mainly based on the number of initiated discussion threads and the associated interanimation. As such, Factor 1R is related to the *individual long-term discourse persistence*. Factor 2R is only composed of the average length of initiated threads, thus describing the *community response to* one's *participation* in the collaborative dialog. Factor 3R mainly includes the social network analysis variables Indegree and Betweenness, as well as the social collaborative dialog quality; therefore, it refers to the *individual communicative centrality*. Factor 4R consists of the variables Eccentricity and Closeness; therefore, it describes the *individual communicative peripherality*.

Cluster Analysis. In the second step of the analysis, the three dimensions resulting from the principal component analysis (Anderson-Rubin method) were used as input for a hierarchical cluster analysis according to the Ward method with quadratic Euclidian distances. The optimal separation of clusters was reached for the following four clusters.

Firstly, Clusters 4 and 3 are most visible due to participants' long-term discourse persistence (Factor 1R) and communicative centrality (Factor 3R). Cluster 4 consists of $n = 2$ participants with very high persistence and centrality, low communicative peripherality, and who yield with their interventions relatively strong community response. Cluster 3 consists of $n = 4$ participants with relatively high persistence and centrality, lowest peripherality, and who yield with their interventions the strongest community response. For these reasons, Clusters 4 and 1 reunite the *central OKC members*, from which Cluster 4 represents the OKC *core group*, and Cluster 3 the *opinion leaders* (possibly in a negative sense as well, e.g., "trolls"), who can fundamentally differ from the core group.

Secondly, Cluster 2 consists of $n = 1859$ blog members with moderate discourse persistence (Factor 1R), yielding moderate to strong community response (Factor 2R), and with moderate centrality (Factor 3R) and moderate, i.e., highest peripherality (Factor 4R). These appear to be the *regular or active OKC members*.

Thirdly and finally, the largest cluster, Cluster 1 (n = 6257) reunites the least active OKC members, with very low discourse persistence (Factor 1R), yielding weakest community response (Factor 2R), and with lowest communicative centrality (Factor 3R) and peripherality (Factor 4R). Hence, Cluster 1 can be described as *peripheral OKC members*.

Integrative versus Non-Integrative Blogger Communities. By comparing the extracted data between integrative and non-integrative blog communities, it appears that integrative OKCs are characterized by stronger peripherality (M = 0.41, SD = 1.34 for integrative, M = −0.18, SD = 0.74 for non-integrative communities, $F(1, 8120) = 642.441$, $p < 0.001$), stronger community response (M = 0.13, SD = 1.13 for integrative, M = −0.06, SD = 0.93 for non-integrative communities, $F(1, 8120) = 60.626$, $p < 0.001$), and somewhat stronger centrality (M = 0.04, SD = 0.71 for integrative, M = −0.02, SD = 1.10 for non-integrative communities, $F(1, 8120) = 4.911$, $p < 0.05$). Significant differences between integrative and non-integrative communities could be found neither in terms of long-term discourse persistence, nor in terms of socio-cognitive structure (i.e., percent of central, active and peripheral members, and relationships between these).

2.4 Discussion and Conclusions

In summary, this study lays the ground for the educational application of OKCs as informal learning environments. This requires in turn that the OKCs integrate the learners in their community discourse. This study assumes that the integrativity of an OKC is tightly connected to the community discourse and practice; hence, it can be assessed by discourse analysis, as follows.

In the first step, the polyphony-based [6] tool ReaderBench [3, 4] was employed to analyze the blog-based OKC discourse. From the multitude of provided results, the following ground dimensions were extracted: (1) individual participants' long-term persistence in the discourse, (2) the community response to their participation, (3) their communicative centrality, and (4) their communicative peripherality within the social network. These dimensions result from Bakhtin's polyphony theory [5] and Trăușan-Matu's analytic approach [6]. They describe the interanimation of voices within a collaborative dialog and appear appropriate for automated discourse analysis.

In the second step, the community members were clustered based on their discourse characteristics. The hierarchical cluster analysis offered a classification including central, active/regular, and peripheral OKC members, which corresponds to the socio-cognitive structures described in the CoP research [2].

In the third and final step, the extracted results were compared between integrative and non-integrative OKCs. While there were no significant differences in terms of socio-cognitive structure, integrative OKCs were associated with significantly stronger communicative peripherality, community response, and communicative centrality.

For educational practice, the conclusions of this study are straightforward: Existing OKCs from the Internet can be used as informal learning environments, for example, in higher education, applying social learning analytics tool such as ReaderBench to optimize the learning activity and make the OKCs "smart" [1, 7]. Appropriate instructional design should be developed and evaluated in the near future. For OKC research, this study adds empirical evidence for the relationship between community discourse and practice.

However, the result validity may be limited by several conceptual and methodological shortcomings. Although the number of participants was fairly high, there was a relatively small number of OKCs involved in the study. Also, integrativity was assimilated to OKC members' response to relatively simple requests. Upcoming research aims to extend both the samples and the perspective on integrativity by observing the long-term interactions between regular OKC members and visitors.

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Chapter 3
SCALE: A Competence Analytics Framework

David Boulanger, Jérémie Seanosky, Colin Pinnell, Jason Bell, Vivekanandan Kumar and Kinshuk

Abstract This paper introduces SCALE, a Smart Competence Analytics engine on LEarning, as a framework to implement content analysis in several learning domains and provide mechanisms to define proficiency and confidence metrics. SCALE's ontological design plays a crucial role in centralizing and homogenizing disparate data from domain-specific parsers and ultimately from several learning domains. This paper shows how SCALE has been applied in the programming domain and reveals systematically how the work content of a student can be analyzed and converted to evidences to assess his/her proficiency in domain-specific competences and how SCALE can also analyze the student's interaction with a learning activity and provide a confidence metric to assess his/her behavior as he/she culminates toward goal achievements.

Keywords SCALE · Competence · Proficiency · Confidence · Learning analytics · Ontological design

3.1 Introduction

This paper proposes an evidence-based competence analytics framework called Smart Competence Analytics engine on LEarning (SCALE). The goal of this research is to feature an approach to competence-based learning applicable to any learning domain. SCALE is mainly concerned with content analysis, one of the key outcomes of learning analytics. However, content analysis is highly domain-specific. SCALE, therefore, through its ontological design attempts to reduce the customization effort and time to a minimum. Although SCALE does not intend to define proficiency and confidence metrics, it aims at providing teachers with the mechanisms to implement their own definitions of proficiency and confidence.

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Thus, SCALE allows real-time customization and calibration of proficiency and confidence models. This paper strives to show the applicability of the framework in any learning domain by applying it in Java programming.

Learning analytics is a study of context-aggregate and context-precise insights based on observed learning experiences that are continually validating in nature where a learning trace comprises of an instantiated network of models that lead to a measurable chunk of learning. In this setting, SCALE provides an important subset of observation data to instantiate those models in order to find causal relationships between those models' variables through a propensity score matching observational study design that will be implemented in a future version.

In the next section, a brief literature review highlights the progress made by other researchers in the employ of ontologies to track by means of e-learning technologies students' competences in programming (i.e., Java). The third section gives a high-level view of SCALE's architecture, while the fourth section shows how SCALE works in the programming domain. The paper concludes by outlining the next steps for a future full-fledged experiment with SCALE.

3.2 Literature Review

Hosseini et al. [1] conducted a study to look at how Java programs are developed. By means of the JavaParser tool, they succeeded to collect unique datasets highlighting the intermediate programming steps through series of snapshots showing how students developed their programs over time. Hosseini et al. performed a fine-grained concept-based analysis on each step to identify the most common programming paths. The results of their experiments showed that students tend to develop and debug their programs incrementally and that tracking intermediate programming steps provide invaluable opportunities to give better feedback to students. Their experiment was conducted in the Java programming domain and used the JavaParser tool "to extract a list of ontological concepts from source code using a Java ontology[1] developed by PAWS laboratory." Those concepts were extracted for each code capture.

Sosnovsky et al. [2] uphold that precise student modeling is key in the effectiveness of adaptive educational systems. Student modeling requires assessing adequately the background knowledge of students before they start using such adaptive systems. Even though this information may be available from other systems, discrepancies most often occur due to different knowledge representation, system architecture, and modeling constraints. Sosnovsky et al. argue "that the implementation of underlying knowledge models in a sharable format, as domain ontologies—along with application of automatic ontology mapping techniques for model alignment—can help to overcome the 'new-user' problem and will greatly widen opportunities for student model translation."

[1] http://www.sis.pitt.edu/~paws/ont/java.owl.

Finally, Ganapathi et al. [3] propose an approach to the practical ontology development and present their approach by designing an ontology to teach Java programming. Researchers in [4–7] rather focus on the identification of common misconceptions and pitfalls in learning programming, while Sampson [8] highlights the role that competence-based learning can play to implement the lifelong learning paradigm.

3.3 SCALE Architecture

SCALE consists basically of three processing layers: parsing, inferencing, and profiling. Moreover, SCALE is built on three types of ontologies: interaction, contents, and learning trace. All learning events collected from a single student engaged in a single learning activity coming from a single learning domain will be parsed and stored in an interaction ontology. The contents ontology models the learning materials, defines learning objectives, and models and maps the skills expected from learners to the learning objectives. The learning trace ontology records measurable subsets of observations into a skill/proficiency with respect to a mapping function. Hence, the mapping between the learning outcomes in the contents ontology and their expected datasets in the learning trace ontology will define a course's expected learning outcomes in terms of proficiency levels in targeted skills.

The first processing layer in SCALE involves the expansion of the student's dataset through domain-specific parsers. For example, analyzing a student's work would imply submitting its work to a series of domain-specific parsers to extract the structure that gives meaning to the student's work. The parsing results are then ontologized and linked to the appropriate captures and constructs extracted from the student's work. Thus, the parsing layer in SCALE requires the integration of domain-specific parsers, the definition of the entities and relationships defining the domain in question, and the specification of the resulting interaction ontology in a universal data format that is an RDF ontology. It is important to highlight the fact that this process can be applied in any domain.

In the second layer of processing, SCALE identifies students' learning artifacts and builds sets of evidences to assess students' proficiency levels in domain-specific competences. SCALE performs competence assessment using pattern matching techniques (domain-specific production rules). SCALE encloses a core set of production rules corresponding to a core set of competences in the learning domain at hand and enables teachers to enhance or customize that set to address the requirements of their courses. The key technology employed by SCALE is called BaseVISor. BaseVISor is an ontological rule-based reasoning engine which extends the system's capability from mere recognition of syntactic and semantic elements in the student's work to the tracking and recognition of creative, design, and logic elements in it. BaseVISor's compact and intuitive XML syntax requires a lower level of expertise to code the production rules. Moreover, since the rules employ the vocabulary defined in SCALE's ontologies, they can be easily written in pseudo-code and implemented by a programmer who is not an expert in the learning domain.

In the third processing layer, SCALE profiles students individually and collectively and provides students with a formative feedback that shows the progression of their proficiency and confidence at different levels of granularity (i.e., learning activity, competence, learning domain).

3.4 SCALE in Programming

This section will give an example of how SCALE can be applied in a specific learning domain. Although at the very moment of this writing SCALE is being customized and applied in English writing and mathematics, this paper will demonstrate the overall process in the programming domain where SCALE has been developed, tested through pilots, and optimized for the first time. As the analytics engine of an overall learning analytics platform, SCALE will receive data from a student enrolled in a Java programming course who is solving an assignment problem using the NetBeans IDE installed with the CODEX plug-in (a plug-in designed along with SCALE to capture the data required for competence analytics) to sense the student's work and transmit it as a learning event to SCALE. CODEX generates such learning events at a regular time interval or every time the student compiles his/her program. Figure 3.1 shows a learning event sensed by CODEX.

In order to be processed by SCALE, data must follow the format of the learning event above. This data packet will first go through the parsing layer. As previously asserted, the content of this packet will be analyzed by a series of domain-specific

StudentID	davidb
Timestamp	1428530086781 (Wed Apr 08 17:55:19 EDT 2015)
Trigger	Timer
FilePath	C:\Users\...\...\NetBeansProjects\Factorial\src\factorial\Factorial.java
Code	(see below)

```
package factorial;
public class Factorial {
  public static void main(String[] args) {
    int num = 8
    System.out.println(""+num+"! = "+factorial(num));
  }
  public static int factorial(int i) {
    if (i == 0) return 1;
    else return i * factorial(i-1);
  }
}
```

Fig. 3.1 A learning event generated from the NetBeans CODEX plug-in parsers. In the current programming domain, the content is parsed by the open source Eclipse JDT compiler (which can be handled programmatically), the single parser being tested as of this writing. The compiler breaks down the code contained in the learning event into an abstract syntax tree and reports about compile-time errors. The parsing results are then ontologized programmatically using the Apache Jena library. The abstract syntax tree along with its inherent connections and dependencies is preserved in the ontology. Figure 3.2 shows a part of the interaction ontology generated from the above learning event. The figure shows how the child/parent relationship preserves the tree data structure of the abstract syntax tree and how each node within the tree is stored along with its properties. The ontology records also the number of compile-time errors pertaining to the current piece of code. Although the most relevant pieces of information are generated in the default configuration of the Eclipse JDT compiler, the Eclipse JDT compiler's configuration could be customized to populate further the interaction ontology in order to enhance SCALE's inferencing capability. The ontologies are written in the RDF/XML format as required by BaseVISor.

The resulting interaction ontology, the output of the parsing layer, will be input in the inferencing layer for the identification of evidences that will prove the student's proficiency in a specific skill. As are the parsers in the parsing layer domain-specific, production rules that define the patterns to recognize proficiency facts will also be domain-specific. The production rules will comply with the set of competences which are mapped to the learning objectives encapsulated in the course's contents ontology. In this first application of SCALE, production rules have been written to match the control structure-related competences as found in the Java OWL ontology (see footnote 1) designed by PAWS laboratory. Proficiency facts recognized by the inferencing layer will be linked to one or more control structure competences. SCALE will also provide a set of core production rules which could be edited or customized by teachers and students at will. New production rules could also be added to enhance the number of competences to be tracked and to increase the ability of the system to track all the flavors or different

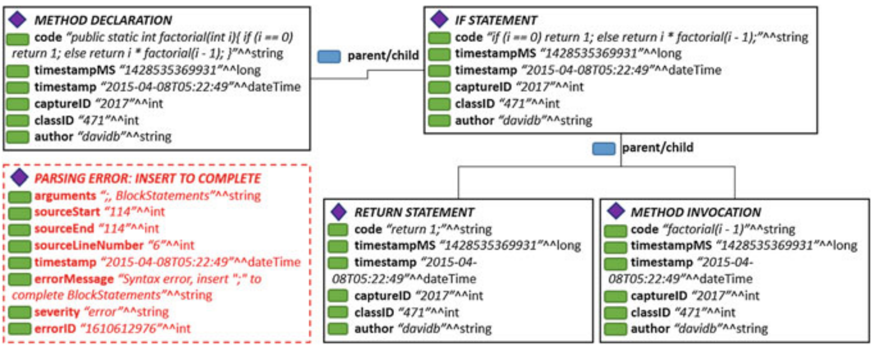


Fig. 3.2 A sample interaction ontology generated from parsing learning event in Fig. 3.1

```
1  <rule name="Recursion">
2      <body>
3          <Individual variable="Var1" rdf:type="interaction:MethodDeclaration">
4              <interaction:code variable="Proof"/>
5              <interaction:author variable="Username"/>
6              <interaction:classID variable="ClassID"/>
7              <interaction:captureID variable="CaptureID"/>
8              <interaction:timestampMS variable="TimestampMS"/>
9              <interaction:timestamp variable="Timestamp"/></Individual>
10         <Individual variable="Var2" rdf:type="interaction:SimpleName">
11             <interaction:child variable="Var1"/>
12             <interaction:code variable="MethodName"/></Individual>
13         <Individual variable="Var3" rdf:type="interaction:Block">
14             <interaction:child variable="Var1"/></Individual>
15         <Individual variable="Var4" rdf:type="interaction:ReturnStatement">
16             <interaction:child variable="Var3"/></Individual>
17         <Individual variable="Var5" rdf:type="interaction:InfixExpression">
18             <interaction:child variable="Var4"/></Individual>
19         <Individual variable="Var6" rdf:type="interaction:ParenthesizedExpression">
20             <interaction:child variable="Var5"/></Individual>
21         <Individual variable="Var7" rdf:type="interaction:MethodInvocation">
22             <interaction:child variable="Var6"/></Individual>
23         <Individual variable="Var8" rdf:type="interaction:SimpleName">
24             <interaction:child variable="Var7"/>
25             <interaction:code variable="MethodName"/></Individual>
26     </body>
27     <head>
28         <assert>
29             <Individual variable="Competence" rdf:type="interaction:Recursion">
30                 <interaction:timestamp variable="Timestamp"/>
31                 <interaction:fact variable="Proof"/></Individual>
32         </assert>
33         <updateProficiency>
34             <param>Recursion</param><param variable="TimestampMS"/>
35             <param variable="Proof"/><param variable="Username"/><param variable="ClassID"/>
36             <param variable="CaptureID"/><param>1</param>
37         </updateProficiency>
38     </head>
39 </rule>
```

Fig. 3.3 The production rule identifying basic cases of recursion in BaseVISor XML syntax

occurrences of a competence or skill. Figure 3.3 shows a production rule identifying a simple application of recursion in the student's code (although not related to control structures).

The reader should note that a production rule is the equivalent of an if/then statement. The "if" part is enclosed in the < body > tags (Lines 2–26) and the "then" part within the < head > tags (Lines 27–38). The "if" part of this recursion rule specifies the sequences and characteristics of programming constructs to identify a case of basic recursion. For example, the rule is looking for a method declaration (Lines 3–9) and stores all its properties into a set of user-defined variables. Basically, this rule checks whether the method declaration is self-invocating (Lines 21–25). As the result of the occurrence of a simple case of recursion, an evidence or fact will be asserted in the ontological model to prove the student's proficiency in that competence (Lines 28–32). Lines 33–37 call a user-defined Java function to interface and store the inferencing results into the SQL and NoSQL world. The parameters from Lines 34–36 pass data from the ontological model to the Java function for further processing or data persistency. The first and last parameters indicate the competence to which this fact corresponds and the weight of the fact which will influence by how much the proficiency value will change according to the mathematical equation defining the competence. As for any production rule, this particular production rule will be fired for each instance of recursion found in a student's program.

The profiling layer will update the proficiency values for those skills the student has showed proper usage and will also update the confidence value of the student in the current learning activity and in the overall programming domain. Table 3.1 lists all the evidences identified from the last learning event. This learning event represents the most recent state of the corresponding learning activity (Factorial.java) recorded by SCALE.

As the next step, SCALE will retrieve all the evidences from the most recent captures of all learning activities it has so far tracked and will sum them up by competence as it can be found in Table 3.2. For example, it can be seen that for student davidb, there have been 12 cases of recursion tracked by SCALE. Using the proficiency function of the Recursion competence, it can be seen that the proficiency level of the student at using recursion is calculated to be 32.61 %. Proficiency and confidence values are always expressed as probabilities, that is, as values between 0 and 1, exclusively (0, 1). It is also interesting to note that teachers can then set a threshold for each competence to determine the learning objective in regard to that competence within their course(s). Moreover, the reader may notice that the StatementBlock and the IfElseStatement competences have proficiency levels very close to each other, while the former competence has twice the number of facts of the later competence. Given the nature of the math (proficiency) functions in Table 3.2 whose ranges lie between 0 and 1 exclusively, capturing the number of facts for each competence will also provide a measure of the persistency of a skill. In other words, it may determine in some way the decay speed of the skill if it was to be unused for a period of time or if misconception or misusage was to be detected.

SCALE also tracks the confidence of students as they work in learning activities. SCALE monitors the student's behavior that is his/her interaction with a learning tool and its learning contents. SCALE provides the mechanism to assess students' confidence both in a learning domain and in a specific activity. Again, SCALE will allow teachers and students to create or customize their own confidence model. Although some factors in the confidence model may be domain-generic such as the time taken to solve a problem, most factors will be domain-specific and will need to be tailored and customized according to the learning domain at hand. Thus, in the current learning domain, that is programming, SCALE provides a predefined confidence model consisting basically of four factors: time spent on a learning activity (writing a program), number of times the student compiles his/her code in a specific learning activity, the average number of errors per compilation for a specific learning activity, and the persistency of those errors throughout a learning activity. SCALE applies the same factors to compute the overall confidence of a student in a learning domain.

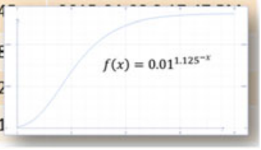
The rationale behind the calculation of a confidence value is that each factor is assessed individually according to the ideal scenario or behavior expected from a

Table 3.1 List of proficiency facts generated from the learning event in Fig. 3.1

FactID	CompetenceName	Username	ClassID	CaptureID	Timestamp	CodeSnippet (proof)	Weight
44894	StatementBlock	davidb	471	2019	2015-04-08 8:17:47 PM	{int num = 8; System.out.println (““ + num +”! = ” + factorial(num));}	1
44895	IfStatement	davidb	471	2019	2015-04-08 8:17:47 PM	if(i == 0) return 1; else return i * factorial(i − 1);	1
44896	IfElseStatement	davidb	471	2019	2015-04-08 8:17:47 PM	if(i ==0) return 1; else return i * factorial(i − 1);	1
44897	StatementBlock	davidb	471	2019	2015-04-08 8:17:47 PM	{if(i == 0) return 1; else return i * factorial (i − 1);}	1
44898	ReturnStatement	davidb	471	2019	2015-04-08 8:17:47 PM	return 1;	1
44899	EqualExpression	davidb	471	2019	2015-04-08 8:17:47 PM	i ==0	1
44900	ReturnStatement	davidb	471	2019	2015-04-08 8:17:47 PM	return i * factorial(i − 1);	1
44901	Recursion	davidb	471	2019	2015-04-08 8:17:47 PM	public static int factorial(int i) {if (i == 0) return 1; else return i* factorial(i − 1);}	1

Table 3.2 Numbers of facts for each competence that will be input in the math function as pictured in the bottom right corner along with corresponding output proficiency levels

Username	CompetenceName	Facts x	Equation $f(x)$	Proficiency	Timestamp
davidb	StatementBlock	121	$f(x) = 0.01^{1.125^{-x}}$	0.999997	2015-04-08 8:17:47 PM
davidb	IfStatement	88	$f(x) = 0.01^{1.125^{-x}}$	0.999854	2015-04-08 8:17:47 PM
davidb	IfElseStatement	63	$f(x) = 0.01^{1.125^{-x}}$	0.99724	[illegible]
davidb	ReturnStatement	45	$f(x) = 0.01^{1.125^{-x}}$	0.97728	[illegible]
davidb	EqualStatement	31	$f(x) = 0.01^{1.125^{-x}}$	0.88732	[illegible]
davidb	Recursion	12	$f(x) = 0.01^{1.125^{-x}}$	0.32611	[illegible]



very proficient student. For example, Student A and Student B have solved the same problem, have both written an excellent piece of software, and have made the same errors with the same level of persistency. However, Student A has taken twice the time of Student B. Hence, naturally, it will be expected that Student B exhibits more confidence than Student A in regard to time. It may, therefore, be inferred that taking less time to solve a problem to meet the requirements of an activity is more desirable than the contrary. The same may be true for the number of compilations a student makes. Similar conclusions could be drawn for each factor in the confidence model.

After having defined the factors making up a confidence model, one could define a threshold for each factor beyond which the confidence of a student in regard to that particular factor would start degrading more significantly. Obviously, the threshold will depend also on the characteristics of the mathematical equation used to model the confidence decay. For example, the mathematical functions defining the confidence factors time and compilations are both quadratic equations. The point here is that SCALE does not want to penalize too much students within an acceptable range of time and number of compilations made when solving a problem. There exists some trade-off between these factors. For instance, a student may decide to compile his/her code more often to reduce the time he/she takes to solve a problem or to correct errors as soon as possible to reduce the number of errors he/she will make in a problem.

Table 3.3 shows the confidence level for each factor and as a whole for the student who has sent the learning event in Fig. 3.1. Figures 3.4, 3.5, 3.6, and 3.7 display the graphs of the mathematical equations determining the value for each confidence factor. Figure 3.4 shows that the input of the equation is the amount of time in terms of minutes. The input in Fig. 3.5 is the total number of compilations made in the learning activity. The input in Fig. 3.6 is the average number of errors per compilation, while the input in Fig. 3.7 is the standard deviation of the numbers of error messages generated for all compilations for that learning activity.

Finally, the confidence measure assigned to that specific learning activity is calculated as the product of the confidence factor values. The ranges of all confidence measurements lie between 0 and 1, inclusively [0, 1]. Hence, SCALE

Table 3.3 Confidence factors along with associated raw data and derived confidence values

Confidence factors	Raw data	Confidence factor values
Duration	720,000 ms = 12 min	0.999856
Number of compilations	3	0.994
Average number of errors	0.6666666666666666	0.9916666666666667
Standard deviation of numbers of errors	0.4841229182759271	0.9096824583655185
Confidence	N/A	0.8965600373460734

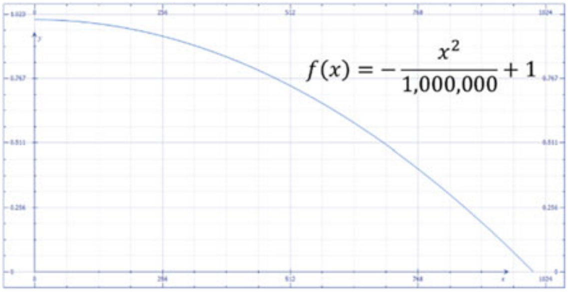


Fig. 3.4 Equation for time confidence factor

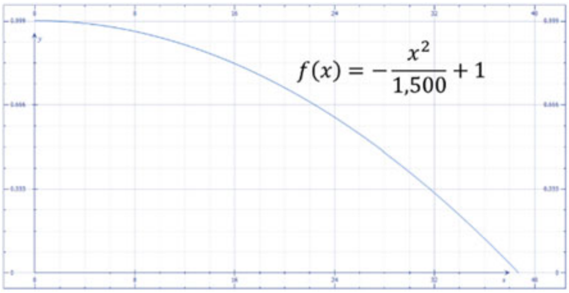


Fig. 3.5 Equation for compilation confidence factor

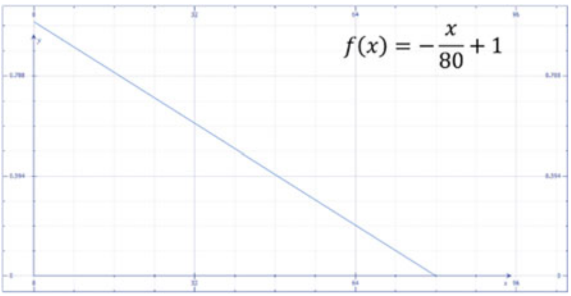


Fig. 3.6 Equation for error confidence factor

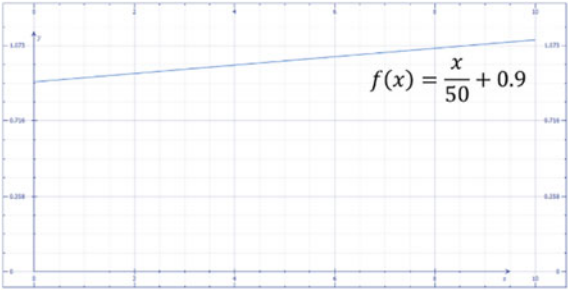


Fig. 3.7 Equation for error persistency confidence factor

assesses that the confidence of student davidb in the learning activity Factorial.java at the moment of the processing of the learning event is as follows:

$$\text{confidence} = 0.9999 \times 0.994 \times 0.9917 \times 0.9097 = 0.8966 \qquad (3.1)$$

The lowest confidence factor will impose a top limit on the overall confidence value.

3.5 Future Work and Conclusion

The scalability and robustness of SCALE are currently being tested at a partner institution in India. SCALE includes mechanisms to monitor thoroughly all the critical processing and input/output (I/O) operations in order to assess its scalability and robustness. In the near future, SCALE will be extended to a full Java course and will be applied in the English writing and mathematics learning domains. Once SCALE will meet all the robustness and scalability requirements to support a full-fledged experiment with a full Java course, a longitudinal propensity score matching observational study will be conducted to evaluate the effectiveness of SCALE over students' learning experiences.

This paper thoroughly described SCALE, an architecture to analyze the proficiency and confidence of students in any learning domain by providing teachers with mechanisms to define their own proficiency and confidence metrics. The paper explains in a step-by-step fashion how to apply SCALE in a learning domain by showing an example in the programming domain.

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Chapter 4
VAT-RUBARS: A Visualization and Analytical Tool for a Rule-Based Recommender System to Support Teachers in a Learner-Centered Learning Approach

Hazra Imran, Kirstie Ballance, Julia Marques Carvalho Da Silva, Kinshuk and Sabine Graf

Abstract Smart learning environments are technology-enhanced educational systems that not only support learners' learning but also provide a learning environment to learners according to their learning needs. In our previous research, we proposed a rule-based recommender system that supports learners in a learner-centered approach (Imran et al. A rule-based recommender system to suggest learning tasks. Springer, Honolulu, 2014). In this chapter, we introduce a visualization and analytical tool for rule-based recommender system (VAT-RUBARS) to provide support to teachers in learner-centered courses. As a result, teachers no longer need to make assumptions about their learners (or courses) and can improve the learning environment to make it more smart and productive for their learners.

Keywords Smart learning environment · Learner-centered learning · Information visualization

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4.1 Introduction

Smart learning environments aim to assist, engage, and enrich the learning experience of learners by providing support to them [2]. In our previous work [1], we developed a rule-based recommender system for learner-centered learning that can be integrated into learning management systems which leads to a smart learning environment, where learners are given support by providing recommendations of learning tasks. Learner-centered pedagogy promotes learners' learning and motivation, and enhances learners' performance [3] by giving more power to the learners, making them independent in acquiring knowledge and, consequently, takes responsibility of their learning. However, there are two main concerns in such pedagogy. The first concern is about whether learners can make good decisions that are appropriate for them in their learning. The second concern is about the difficulty for teachers to plan and design a productive learner-centered learning environment as well as monitor and understand learners' behavior in such environment. The first concern was addressed by the recommender system that supports learners in a learner-centered environment, as reported in our previous research [1]. To address the second concern and to make learner-centered environments more productive, this chapter introduces the visualization and analytical tool for rule-based recommender system (VAT-RUBARS).

The remainder of the chapter is structured as follows: Sect. 4.2 presents related work. Section 4.3 discusses VAT-RUBARS and introduces its indicators in detail. Section 4.4 concludes the chapter by summarizing the main contributions of our work and presenting future directions.

4.2 Related Work

Learning management systems gather a lot of data related to learners' interactions with the system. These data are very important as it provides information about learners' behavior. Previously, the data tracked by learning management systems were mainly used to provide support to learners [4]. More recently, there is an emerging interest in using such data to support teachers with the goal of providing information about the course and learners through meaningful visualizations. In this section, we describe the previous research works related to analytical tools that provide support to teachers.

Mazza and Botturi [5] designed GISMO for Moodle to support teachers by displaying learners' tracking data through graphs based on log data. Teachers can look at graphs and examine learners' social, cognitive, and behavioral interactions in a course. The social interactions show how learners are participating in discussions while cognitive interactions focus on the learners' performance in quizzes and assignments. The behavioral interactions deal with the learners' access to the course. Likewise, Jovanovic et al. [6] presented a tool, LOCO-Analyst, to provide feedback to teachers related to their learners' learning process in Web-based learning environments. The tool mainly shows three types of information: activities performed by the learners, usage of learning content, and social interactions among learners. Govaerts et al. [7] developed Student Activity Meter (SAM) to provide visualizations of learner actions. SAM can help teachers in identifying learners who are doing well or are at risk. The tool uses two metrics: time spent and resource use. Through time spent, teachers can see the time learners who are spending on activities in a course and can compare it with their expectations. Resource use can give information about how often particular resources are used by the learners.

Currently available tools, such as the examples above, mainly focus on visualizing learners' performance and interaction data, and identifying learners at risk. The tool proposed in this chapter, on the other hand, focuses on supporting teachers in a learner-centered setting, with focus on showing how learners perform and behave in such setting. Furthermore, teachers can use VAT-RUBARS to investigate the behavior of the learners with similar characteristics (such as learners with certain learning styles, prior knowledge level).

4.3 VAT-RUBARS

VAT-RUBARS uses graphs and tables for visualization. Along with these techniques, cues such as color and linking are used. For example, information is represented using three colors (red, yellow, and green) where red indicates that attention from a teacher is needed, yellow means attention might be needed, and green means that everything is going well. Figure 4.1 presents an interface of VAT-RUBARS. Different types of visualizations, called indicators, are shown in different tabs. Teachers can select the levels at which they want to see the information, distinguishing between an overall category where information about the whole class is presented, and an individual category where information about a single learner is presented. For each of these categories, a filter panel provides teachers with the functionality to set filters as needed. For the overall category, five filters (unit, difficulty level, expertise level, prior knowledge, and learning styles) are provided, while for individual learners, two filters (unit and difficulty level) are available. In the next subsections, each of the five indicators is discussed in further detail. While Fig. 4.1 shows the overall tool with the filter panel, subsequent figures will only show the visualizations displayed for each indicator, without the filter panel.

4.3.1 Unit-Related Performance

The first indicator is about unit-related performance (Fig. 4.2). For each unit, the performance of tasks is calculated as the average grades of a particular learner, a

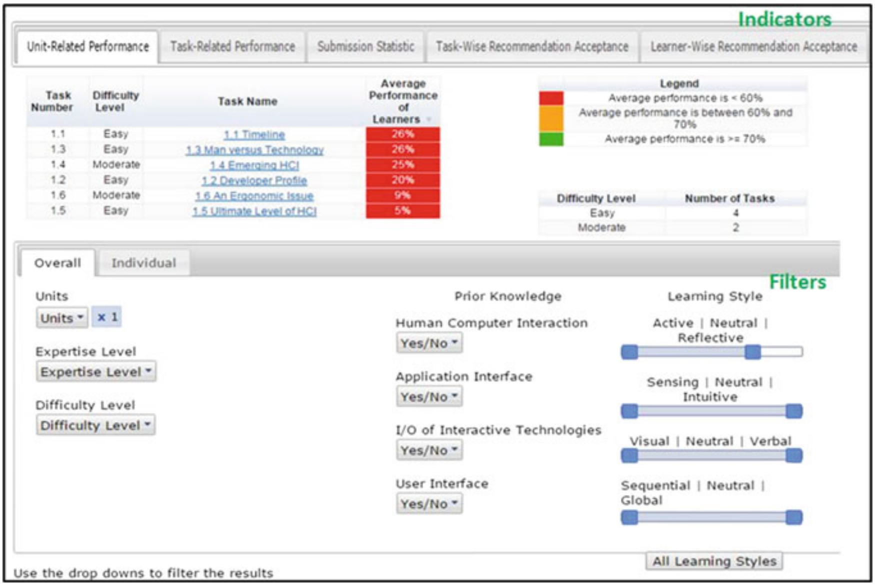

Fig. 4.1 General view of VAT-RUBARS

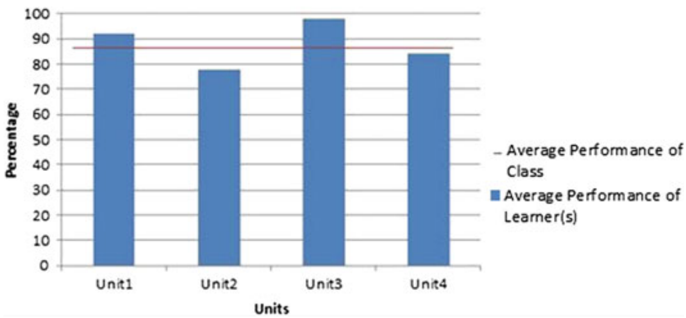

Fig. 4.2 Unit-related performance indicator

group of learners or all learners. The overall average performance of the whole class on all tasks is plotted on the graph as red line, so that teachers can see in which units the performance is higher/lower than the average performance of the whole class.

The indicator can help teachers in understanding in which unit the class, a particular learner or a group of learners, is not performing well. Accordingly, a teacher can further look into the tasks that are present in the respective unit.

Task Number	Difficulty Level	Task Name	Average Performance
1.1	Easy	1.1 Timeline	40%
1.2	Easy	1.2 Developer Profile	69%
1.3	Easy	1.3 Man versus Technology	86%
1.4	Moderate	1.4 Emerging HCI	61%
1.5	Easy	1.5 Ultimate Level of HCI	57%
1.6	Moderate	1.6 An Ergonomic Issue	90%
2.1	Challenging	2.1 Research and Report on Rapid Interface Design Tools	20%
2.2	Challenging	2.2 Install and Test a Freeware Voice Command/Dictation Program	98%

Legend
Average performance is < 60%
Average performance is between 60% and 70%
Average performance is >= 70%

Difficulty Level	Number of Tasks
Challenging	6
Easy	9
Moderate	7

Fig. 4.3 Task-related performance indicator

4.3.2 Task-Related Performance

The "Task-Related Performance" indicator, shown in Fig. 4.3, supports teachers in getting information about how the overall class, a group of learners, or an individual learner performed in each task. The tasks are displayed in three colors (green, yellow, and red) based on the threshold values which can be set by a teacher. If these values are not set by a teacher, default values are used (i.e., 70 and 60 %). Different colors help teachers to see easily the tasks in which the learners are not performing well. Teachers can use this information to further investigate whether these tasks might need some revisions.

4.3.3 Submission Statistic

With the help of the "Submission Statistic" indicator, shown in Fig. 4.4, teachers can identify the frequency by which various tasks have been submitted by the learners. Again, how often tasks have been selected for being submitted by the

Task Number	Task Level	Task Name	Frequency of Submission
1.1	Easy	1.1 Timeline	86%
1.4	Moderate	1.4 Emerging HCI	10%
2.4	Easy	2.4 Describe a Specific Computer-managed Manufacturing Process	56%
3.1	Easy	3.1 Describe Graphical User Interfaces – Windows	45%
4.5	Challenging	4.5 Learn and Use a Programming Interface – Logo	15%

•	Submitted by more than 60% of all learners
•	Submitted 20% to 60% of all learners
•	Submitted by less than 20% of all learners

Fig. 4.4 Submission statistic indicator

learners is visualized by using three colors (i.e., green, yellow, and red), where green means that a task has been submitted very often, yellow means that a task has been submitted sometimes, and red means that a task has been submitted rarely.

Similar to the "Task-Related Performance" indicator, default values are used (i.e., 20 and 60 %) for the thresholds on which to display a task in green, yellow, or red. This information provides teachers with insights into which tasks are often selected and which tasks are less or not at all selected.

4.3.4 Task-Wise Recommendation Acceptance

The "Task-Wise Recommendation Acceptance" indicator, shown in Fig. 4.5, gives an overview about the learners' behavior toward recommendations provided to them through the rule-based recommender system. This indicator provides information about (1) the number of learners who selected a particular task in their initial plan; (2) the number of learners to whom the particular task has been recommended; and (3) the number of learners who actually submitted that task. This indicator can help teachers in understanding why learners have selected a particular task and whether or not they followed the recommendations provided by the recommender system.

4.3.5 Learner-Wise Recommendation Acceptance

The "Learner-Wise Recommendation Acceptance" indicator, shown in Fig. 4.6, represents how often the learners accepted task recommendations by the recommender system, per learner and unit of the course. With this indicator, teachers can investigate the behavior of the learners toward the recommendations given by the

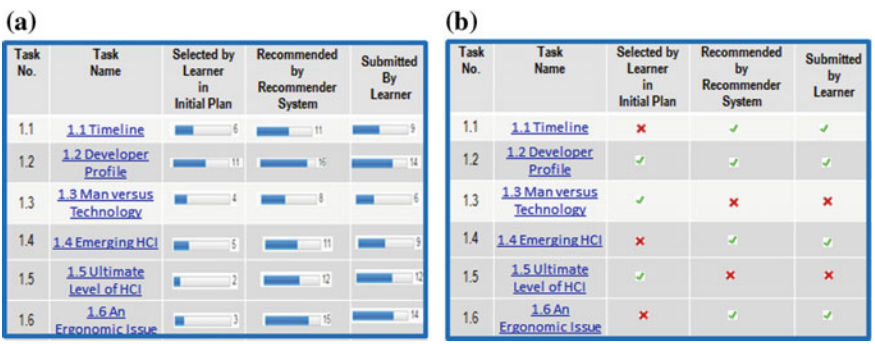

Fig. 4.5 Task-wise recommendation acceptance indicator. **a** Overall class. **b** Individual learner

Names	Acceptance Rate			
	Unit 1	*Unit 2*	*Unit 3*	*Unit 4*
Learner 1	80%	40%	60%	70%
Learner 2	50%	40%	80%	20%
Learner 3	10%	40%	80%	80%

Fig. 4.6 Learner-wise recommendation acceptance indicator

recommender system. This acceptance rate provides teachers with information on how well the recommender system is accepted by the learners.

4.4 Conclusion and Future Work

This chapter presented VAT-RUBARS, a visualization and analytical tool for rule-based recommender system. The main aim of this tool is to support teachers in smart learning environments by providing them with functionality to reflect on their teaching practices in courses that apply a learner-centered design, where learners can select learning tasks and are provided with recommendations of such learning tasks. VAT-RUBARS provides valuable information based on five indicators: unit-related performance, task-related performance, submission statistics, task-wise recommendation acceptance, and learner-wise recommendation acceptance.

In future work, we will extend VAT-RUBARS by adding a recommendation component for the teachers. This recommendation component will provide recommendations to teachers (e.g., tasks which should be revised) based on the information currently presented to them.

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Chapter 5
Improving Learning Style Identification by Considering Different Weights of Behavior Patterns Using Particle Swarm Optimization

Jason Bernard, Ting-Wen Chang, Elvira Popescu and Sabine Graf

Abstract Matching the course content to students' learning style has been shown to benefit students by improving their learning outcome, increasing satisfaction, and reducing the time needed to learn. Consequently, an accurate method for identifying these learning styles is of a high importance. Up to the present, there have been proposed several such methods that use students' behavior in online courses to automatically identify their learning style. However, the precision of existing approaches peaks at approximately 80 %, thus leaving room for improvement. This paper introduces a novel approach, which combines the advantages of artificial/computational intelligence and rule-based techniques. More specifically, a rule-based method is extended to consider the different weights of behavior patterns using a particle swarm optimization algorithm. The approach has been evaluated with 75 students, and results show improved performance over similar state-of-the-art methods. By identifying learning styles with higher precision, students can benefit from adaptive courses that are tailored more precisely to their actual learning styles and teacher can benefit by being able to provide students with more helpful interventions.

Keywords Particle swarm optimization · Felder-Silverman learning style model · Identification of learning styles · Learning management systems

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5.1 Introduction

Adapting the educational experience to students' preferences and needs is an important objective of current technology-enhanced learning systems. Learning style is one of the individual characteristics which need to be taken into account, as it encompasses the strategies and preferences used by a student to approach the learning process [1]. While there have been some controversy and open questions around this concept [2], numerous studies have shown that matching the course content to students' learning styles leads to benefits such as better performance, higher learning satisfaction and a reduction in the time needed to learn [3–5].

For example, Popescu [3] found that students' perceived learning satisfaction was higher in case they followed a course which matched their learning styles (as compared to a course that did not match their learning styles). In another study, Ford and Chen [4] obtained an absolute gain in quiz scores by matching learning materials to students' learning styles. Furthermore, Graf et al. [5] reported a decrease in the study time for active and sequential learners, when provided with a course that matched their learning styles.

In this context, in the current paper we focus on the identification of learning styles, as the first step toward providing the required adaptation. Among the many learning style models proposed in the literature, we selected the Felder-Silverman model (FSLSM) [1], due to several reasons. FSLSM uses four learning style dimensions: active/reflective (A/R), sensing/intuitive (S/I), visual/verbal (V/V), and sequential/global (S/G), with the assumption that each learner has a preference on each of the four dimensions. By using dimensions rather than types (as done in many other learning style models), students' preferences can be described more accurately and in more detail. Additionally, FSLSM treats learning styles as tendencies, rather than immovable characteristics. Another advantage of this model is the existence of a reliable measuring instrument, called Index of Learning Styles Questionnaire (ILS) [6]. As a result of the questionnaire, the learning style of the student is described on a scale between −11 and +11 (with steps of ±2) for each FSLSM dimension; hence, the strength of the preference is determined as well. For all these reasons, FSLSM seems to be one of the most often used learning style models in technology-enhanced learning and some researchers have argued that this model is one of the best or even the best model to use in adaptive systems [7, 8].

While the ILS questionnaire has been found to be a reliable and valid instrument to identify learning styles [9], there are some significant drawbacks of using questionnaires in general. For example, filling in the questionnaire requires a supplementary amount of work from the part of the students and it may be difficult to motivate them to answer it carefully, without skipping questions or giving wrong answers on purpose. Besides being intrusive, the student's mood or perceived importance of the questionnaire may influence the outcome. Finally, since the same questionnaire cannot be repeatedly applied, the student model is created only once at the beginning of the course, without the possibility to be updated later on [10].

In order to avoid these drawbacks, research has been conducted on automatically identifying students' learning styles by analyzing their behavior in online or blended courses [11–17]. However, there is still room for improvement with respect to the precision of the modeling methods. Therefore, in this paper we propose a novel approach called Learning Style Identifier based on Particle Swarm Optimization (LSID-PSO), which aims to outperform existing methods. LSID-PSO is designed to be used in any learning system since it is based on generic student behavior data as input.

The remainder of the paper is structured as follows: Sect. 5.2 presents other automatic approaches used to identify learning styles. Section 5.3 provides a brief introduction into particle swarm optimization. Section 5.4 explains the performance metrics used to assess LSID-PSO. Section 5.5 provides details on how LSID-PSO is used to identify learning styles and the methodology employed to evaluate it. Section 5.6 reports and discusses the results of the evaluation and compares them to other studies. Lastly, Sect. 5.7 concludes the paper.

5.2 Related Work

Recently much research has been done on automatic approaches to identify students' learning styles from their behavior in a course. The approaches can be broadly classified into two categories: artificial/computational intelligence (AI/CI) and rule-based. With respect to the AI/CI category, Dorça et al. [11] proposed the use of a reinforcement learning algorithm to dynamically identify learning styles but only evaluated their approach with simulated data. Garcia et al. [12] introduced a Bayesian approach which considered three of the four FSLSM dimensions and resulted in precision values between 58 and 77 %. Cha et al. [13] evaluated a decision tree and hidden Markov model and found error rates between 0 and 33 %. However, they only used data indicating a strong preference on a specific learning style dimension rather than including all data, and therefore, their approach can only classify a subset of learners. Özpolat and Akar [14] used data mining to extract training data from student behavior logs and construct decision trees. Their evaluation showed accuracy rates between 53 and 73 %. Furthermore, in our previous work [15], we used artificial neural networks considering a set of behavior patterns which are general to any learning system. This approach showed a range of precision from 79 to 84 %.

The rule-based approaches work by using predefined rules extracted from the literature to compute learning styles based on behavior patterns. The advantage of these approaches over AI/CI ones is that the rules are encoded prior to data collection, so no training of the approach is necessary. An example of such rule-based system is DeLeS, developed by Graf et al. [16], which is able to identify FSLSM dimensions with precision from 73 to 79 %. Another rule-based approach, WELSA, for the unified learning styles model (ULSM) obtained precision between 64 and 84 % [10]. The Oscar conversational intelligent tutoring system [17] also uses a rule-based approach. However, it employs data from a natural language dialog between the student and the system instead of behavior data, making the approach quite uniquely applicable to the respective system. Based on an evaluation, accuracy values of 72–86 % were achieved.

While rule-based approaches are very successful, a major drawback is that they assume that all behavior patterns are equally important. Relative importance may be implemented by weighting the patterns [10]; however, such weights are not easily extracted from the literature. LSID-PSO aims at addressing this issue by extending a rule-based approach with artificial/computational intelligence features to search for optimal weights of behavior patterns, using particle swarm optimization.

5.3 Particle Swarm Optimization

Particle swarm optimization (PSO) [18] is an algorithm, inspired by the movement of flocks of birds, designed to efficiently search an n-dimensional hyperspace, or hypershape when the space is bounded, for optimal solutions. PSO uses search by social intelligence as the population of particles share information as they fly through the space and adjust their trajectories to focus on promising areas. The n-dimensional location of a particle represents a solution to a problem and the particles' movement through the space represents their search for optimal solutions. Each coordinate of a particle's location represents a component of the solution although the decoding of the coordinate to the solution component is problem specific.

PSO is highly parameter driven as with many AI/CI algorithms. Without proper parameter selection, particle swarm optimization can suffer from inefficient trajectories that may prevent convergence to the optimal solution [19]. The parameters in particle swarm optimization are: population size, individual and global acceleration rates (c_1 and c_2), inertia (w), and maximum velocity ($V_{\max}$). The parameters and their effects, as described below, come from the original [18] and follow-up works [19, 20]. The population size is the number of particles in the swarm. The global acceleration rate encourages the particles to turn toward the global best solution, while the individual best acceleration rate causes the particles to turn toward their individual best. Inertia causes the particle to continue in the same direction so a higher inertia encourages global exploration. The maximum velocity prevents the particles from flying too far from promising areas; however, if it is set too low the particles will not be able to search very globally for promising areas to begin with. In each generation, each particle's velocity is updated using Formula 5.1, where V_0 is the previous generations velocity, rand is a random real value from 0 to 1, X_{curr} is the particle's current position, X_{pbest} is the individual's best position so far, and X_{gbest} is the global best position so far.

$$V = w \times V_0 + c1 \times \text{rand} \times \left(X_{\text{curr}} - X_{\text{pbest}}\right) + c2 \times \text{rand} \times \left(X_{\text{curr}} - X_{\text{gbest}}\right) \quad (5.1)$$

5.4 Performance Metrics

Four metrics are used to demonstrate the performance of LSID-PSO and compare its results to results from the literature. The first metric is SIM, which is commonly used for measuring the performance of learning style identification [12, 14–16]. A normalized range from 0 to 1 is used to describe each dimension of the students' learning style. Thus, values higher than 0.5 represent a tendency toward an active, sensing, visual, or sequential learning style and values lower than 0.5 represent the opposite preference (i.e., reflective, intuitive, verbal, or global). The SIM function divides the learning style range into a high region (>0.75), a low region (<0.25), and a balanced region (0.25–0.75). SIM returns 1 when the actual and identified learning style values are in the same region, 0.5 when they are in adjacent regions, and 0 when they are in opposite regions. SIM values are calculated for each student and then an average SIM value is built to measure the accuracy of the learning style identification approach.

While SIM is commonly used in the literature, it has a drawback of reduced accuracy due to classifying results into regions. While some identification approaches return learning style regions as results (e.g., Bayesian networks), LSID-PSO is capable of returning precise learning style values. Accordingly, we are able to measure the exact difference between the results from LSID-PSO and the actual learning style value, leading to a more accurate performance metric, which we call ACC. As with SIM, ACC is calculated for each student and an average ACC is built. ACC can measure the performance more accurately than SIM, especially when the actual and/or identified learning style values are near the region edges.

While the above-mentioned performance metrics provide details on how accurate the proposed approach is on average, in the current research we aim to also investigate the accuracy of learning style identification for each single student. To further investigate this "fairness problem," two additional metrics are introduced: (i) LACC is the lowest ACC value within a set of students; (ii) %Match measures the percentage of students which are identified with ACC > 0.5, showing how many students have been identified with reasonable accuracy. Both of these metrics provide deeper insights into whether some of the students are identified with significantly low accuracy.

5.5 Methodology

In order to evaluate LSID-PSO, data from 127 information system/computer science undergraduate students were collected, including their behavior data in a university course as well as their results on the ILS questionnaire. Only students who submitted more than half of the assignments, and attended the final exam were considered for this study. In addition, only data from students who spent more than 5 min on the ILS questionnaire were used. This led to a dataset of 75 students. It should be noted that this dataset is, in comparison with related studies, one of the largest datasets (e.g., Garcia et al. used 27 students [12] and Özpolat and Akar used 30 students [14]).

This research treats each FSLSM dimension as a separate problem, and therefore, a separate LSID-PSO algorithm is developed and applied for each dimension. The first step in developing LSID-PSO is to determine the behavior patterns related to that learning style dimension. As LSID-PSO aims at being applicable in different learning systems, it was important to use generic behavior patterns so that data can be collected in various systems. Therefore, we decided to use the same behavior patterns employed by DeLeS [16], as shown in Table 5.1. These patterns were retrieved from the learning styles literature [1] and, while a short description of the most relevant patterns is provided in the next paragraph, a more detailed discussion is provided in the study by Graf et al. [16]. While in DeLeS, each behavior pattern is considered equally important, LSID-PSO starts from the hypothesis that learning style identification may be improved by weighting the behavior patterns.

The patterns are based on different types of learning objects including outlines, content, examples, self-assessment quizzes, exercises, and forums; students' navigation sequence through the course is also taken into account. Patterns consider how long a student stayed on a certain type of learning object (e.g., *content_stay*) and how often a student visited a certain type of learning object (e.g., *content_visit*). Furthermore, questions of self-assessment quizzes were classified based on whether they are about facts or concepts, require details or overview knowledge, include graphics or text only, and deal with developing or interpreting solutions. Patterns then consider how well students performed on such types of questions (e.g., *question_concepts*).

LSID-PSO needs a solution space to search, so a hypercube is created with n-dimensions, each bounded from 0.01 to 1.0, where n is the number of behavior

Table 5.1 Behavior patterns for learning style identification [16]

Active/reflective	Sensing/intuitive	Visual/verbal	Sequential/global
content_stay	content_stay	content_visit	outline_stay
content_visit	content_visit	forum_post	outline_visit
example_stay	example_stay	forum_stay	question_detail
exercise_stay	example_visit	forum_visit	question_develop
exercise_visit	exercise_visit	question_graphics	question_interpret
forum_post	question_concepts	question_text	question_overview
forum_visit	question_details		navigation_overview_stay
outline_stay	question_develop		navigation_overview_visit
quiz_stay_results	question_facts		navigation_skip
self_assess_stay	quiz_revisions		
self_assess_twice_wrong	quiz_results_stay		
self_assess_visit	self_assess_stay		
	self_assess_visit		

patterns in the learning styles dimension. Each hypercube dimension represents a weight from 0.01 to 1.0, with zero excluded as the effectiveness of DeLeS suggests that the behavior patterns identified for each learning style dimension have at least some impact. From this, a particle's location can be decoded as a set of weights for patterns corresponding to a learning style dimension.

In order to operate effectively, PSO's parameters must be properly set and although some general principles [18–20] are known and used for the suggested values below, optimal parameterization is problem specific. Accordingly, the following parameters were optimized in the given order by experimentation: population size, acceleration rates, inertia, and maximum velocity. Although population size is generally less than 100 [18–20], in order to maximize the chance of optimization the range of values assessed was extended to (25, 50, 75, 100, 200, 400). The individual acceleration parameter (*c1*) was tested with values from the set (0.0, 0.25, 0.5, 0.75, 1.0) and the global acceleration parameter (*c2*) from the set (0.25, 0.5, 0.75, 1.0). As the global best must always be considered, *c2* is not assigned a value of zero. Although the suggested inertia range is 0.9–1.2 [20], to allow for the greatest chance of optimization the set was expanded to (0.75, 0.9, 1.0, 1.1, 1.2). It is recommended that V_{max} be made equal to the size of the hypershape bounds (X_{max}) [19]. In the current research, the bounds are the weight minimum (0.01) and maximum (1.0) values, hence $X_{max} = 0.99$. Values of $V_{max} > X_{max}$ were not assessed, as if a particle's velocity (v) is greater than X_{max}, it has the same effect as $v = X_{max}$, the particle will hit the hypershape boundary. In addition to assessing $V_{max} = X_{max}$, values smaller than X_{max} were assessed. Accordingly, possible V_{max} values were obtained by multiplying X_{max} by a factor from the set (0.05, 0.10, 0.25, 0.50, 1.00) giving a final set of V_{max} values of (0.0495, 0.099, 0.2475, 0.495, 0.990). Table 5.2 shows the optimal parameters obtained for each dimension.

With AI/CI algorithms there often exists the potential for overfitting, where solutions are fit to noise of the training data and so the found solution is not a general one. There exist numerous techniques for reducing overfitting; in case of LSID-PSO, we used stratification [21] which ensures that the training set and assessment set have a similar distribution of data, thus causing the solution to be more general toward future samples. After parameter optimization, the use of stratification was investigated. Stratification was found to improve the results for each learning styles dimension and therefore was used to produce the final results.

Table 5.2 Optimal parameter settings

FSLSM dimension	Population	Acceleration		Inertia	V_{max}
		Global	Individual		
A/R	400	1.00	1.00	0.75	0.990
S/I	100	1.00	0.25	1.20	0.990
V/V	400	1.00	0.50	1.00	0.099
S/G	50	1.00	1.00	0.90	0.495

A 10-fold cross-validation approach was used to ensure that the results are generalizable to other datasets. This approach was employed for parameter optimization, investigations on the overfitting reduction techniques and to calculate the final results.

5.6 Results and Discussion

In this section, we discuss the results of LSID-PSO and compare them to similar approaches (as identified in Sect. 5.2). While there are several other works that introduced approaches to identify learning styles, it was difficult to compare some of these approaches to ours. A comparison with the approach by Cha et al. [13] is not possible as their approach is only tailored to students with a strong preference on a learning style dimension rather than identifying learning styles from every student. Comparing results to Oscar [17] is not applicable as this approach focuses on identifying learning styles from natural language dialogs, whereas LSID-PSO (and most other works) focuses on identifying learning styles from behavior patterns in courses.

Table 5.3 shows a comparison of the SIM results between LSID-PSO and other approaches in the literature which use SIM. We can notice that LSID-PSO performs well compared to the other approaches: it achieved the second best results for the A/R, V/V, and S/G dimensions and the third best result for the S/I dimension.

Since the SIM metric is not as accurate as ACC and we also aim at investigating the mismatches of single learners, raw results from DeLeS and LSID-ANN were obtained to calculate ACC, LACC, and %Match (as these two approaches achieved the best results in two dimensions each and therefore seem to be the leading approaches). By comparing results from LSID-PSO with results from DeLeS and LSID-ANN based on the ACC, LACC, and %Match metrics, more accurate information can be provided on how well LSID-PSO performs. Table 5.4 shows these results.

In the A/R dimension, LSID-PSO achieved the best results with respect to ACC and %Match, while it obtained rank 2 for LACC. For S/I, LSID-PSO also achieved the highest ACC and %Match values, and again rank 2 for LACC. For V/V,

Table 5.3 Comparison of SIM results (with ranks in parentheses and top result bolded)

Approach	A/R	S/I	V/V	S/G
LSID-PSO	0.801 (2)	0.755 (3)	0.756 (2)	0.810 (2)
LSID-ANN [15]	**0.802 (1)**	0.741 (4)	0.727 (3)	**0.825 (1)**
DeLeS [16]	0.793 (3)	**0.773 (1)**	**0.767 (1)**	0.733 (3)
Bayesian [12]	0.580 (5)	0.770 (2)	–	0.630 (4)
NBTree [14]	0.700 (4)	0.733 (5)	0.533 (4)	0.733 (3)

Table 5.4 Comparison of ACC, LACC, and %Match metrics between LSID-ANN [15], DeLeS [16], and LSID-PSO

Dimension	Approach	ACC	LACC	%Match
A/R	LSID-PSO	**0.805 (1)**	0.596 (2)	**0.988 (1)**
	LSID-ANN	0.802 (2)	**0.610 (1)**	0.986 (3)
	DeLeS	0.799 (3)	0.435 (3)	0.987 (2)
S/I	LSID-PSO	**0.794 (1)**	0.551 (2)	**0.971 (1)**
	LSID-ANN	0.790 (2)	**0.575 (1)**	0.961 (2)
	DeLeS	0.790 (2)	0.389 (3)	0.960 (3)
V/V	LSID-PSO	0.796 (2)	0.482 (2)	0.909 (3)
	LSID-ANN	**0.840 (1)**	**0.656 (1)**	0.986 (2)
	DeLeS	0.788 (3)	0.226 (3)	**0.987 (1)**
S/G	LSID-PSO	0.768 (2)	0.524 (2)	0.943 (2)
	LSID-ANN	**0.797 (1)**	**0.613 (1)**	**0.986 (1)**
	DeLeS	0.702 (3)	0.134 (3)	0.880 (3)

LSID-PSO produced overall lower values, with rank 2 for ACC and LACC and rank 3 for %Match. In S/G, LSID-PSO was constantly on rank 2 for all metrics. Overall, it can be seen that LSID-PSO performed better than other approaches for A/R and for S/I: it reached the best ACC results and the best %Match results, however, for LACC, it performed better than DeLeS but not as well as LSID-ANN. For V/V and S/G dimensions, LSID-PSO performed better than DeLeS (apart from the %Match metric in V/V) but not as well as LSID-ANN. As the hypothesis is that weighting the behavior patterns would ameliorate results over no weighting, the comparison to DeLeS confirms it: weighting did improve results in every dimension for every metric, with the exception of %Match for V/V.

In order to understand the lower %Match value for V/V dimension, the individual mismatches were examined. We discovered that all of the mismatched students had a verbal learning style. It seems that LSID-PSO tend to correctly match the more numerous visual students (85 % of the total), at the cost of less precision with verbal students, in order to obtain a better average ACC.

Although LSID-PSO confirmed the hypothesis, it converged very quickly, often in less than 100 generations, raising the concern that it may not be searching very well. To address this concern, the particle trajectories were examined and two observations were made. When the global and individual best were distant, a flat oscillation was observed between the two points. When the individual and global best were close, the particles orbited a center between the global and individual best. Although the center did shift considerably, rarely would the particles pass close to the global or individual best. So although LSID-PSO performed well, a different optimizer could be considered for the problem to see whether it can search the solution space better.

5.7 Conclusions

In this paper, an approach (LSID-PSO) for automatically identifying students' learning styles based on Felder-Silverman Learning Style Model is introduced. LSID-PSO was assessed using different performance metrics and evaluated with real data from 75 students. The results were compared to other approaches in the literature and based on the most accurate performance metric (ACC), LSID-PSO produced the highest precision values for the A/R and S/I dimensions. In addition to measuring the average precision of the approaches, this study investigated how often single students are significantly misidentified via the two metrics LACC and %Match. In this regard, for LSID-PSO, the results are mixed: although it mostly did not provide an improvement compared to LSID-ANN (except for %Match for A/R and S/I), it did outperform DeLeS, except for %Match for V/V. Overall, the results from LSID-PSO confirm that extending the rule-based approach by considering weights for behavior patterns provides an improvement in the learning style identification.

In future work, other optimizers such as ant colony system will be investigated to see whether they can search more effectively and find a more optimal set of weights. Hybrid AI algorithms can also overcome weaknesses in mono-AI algorithms and will be investigated to see whether they can find better solutions than PSO alone.

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Chapter 6
Designing Mobile Games for Improving Self-esteem in Children with ADHD

Nilufar Baghaei, John Casey, Yvette Ahmad, Hai-Ning Liang and Zhen Yu

Abstract There are a growing number of children with attention-deficit/hyperactivity disorder (ADHD). Research has shown that these children process information quite differently from others. A lot of ADHD-diagnosed children (especially inattentive type ADHD) are more of a visual learner, easily distracted, struggle to follow instructions, are easily forgetful and more importantly have low self-esteem. Parents are often overwhelmed by the amount of information they receive on how to handle their child's symptoms and learning style. In this project, we propose a novel way to increase the self-esteem of ADHD-diagnosed children through use of computer games. We came up with a set of design principles that can be applied to any game to make it suitable for ADHD children, especially with the aim of increasing their self-esteem. Our game design was applied to an existing open-source mobile game (GLtron). The results of a pilot study showed that users enjoyed playing the game and found it valuable for increasing players' self-esteem.

Keywords Game design · Self-esteem · Engagement · Attention-deficit disorder · Hyperactivity

6.1 Introduction

The term attention-deficit/hyperactivity disorder "ADHD" is applied to anyone that meets the diagnostic and statistical manual of mental disorders (DSMV) test criteria [1–3] and stands for attention-deficit/hyperactivity disorder. A growing number of

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children are diagnosed with ADHD. They are affected by a range of problematic behaviours such as distractibility, hyperactivity and difficulty to stay focused or following orders. They sometimes present aggressive behaviour, social isolation and defiance to teachers and parents. If a child is diagnosed with ADHD, it does not mean that he/she has all these symptoms [2, 4]. Nylund mentions in his book "Treating Huckleberry Finn" [5] that the traditional ways of teaching do not work very well on ADHD-diagnosed children. They need a more dynamic way of interaction, which could help them maintain their focus.

Treatments range from stimulant medication to cognitive behaviour therapy to behavioural strategies. Parents are often overwhelmed by the amount of information they receive on how to handle their child's symptoms and learning style. Research has shown that the standard parenting skills do not work with ADHD child, as they process information quite differently from other children [2, 3, 6, 7]. For example, they are more visual learners than verbal learners. A lot of ADHD-diagnosed children (especially inattentive type ADHD) are easily distracted, struggle to follow instructions, are easily forgetful and more importantly have low self-esteem [1–3, 7]. What they need is short and concise verbal instructions and immediate feedback as well as constant positive feedback, even if they only get it partially correct.

In this project, we proposed a novel way to increase the self-esteem of ADHD-diagnosed children through use of computer games. Previous research [8] has shown that educational video games, if successfully implemented, can provide users with academic success, cognitive abilities (stimulation of different abilities like creativity), motivation, and attention and concentration. With the help of our external partner, who is a registered clinical psychologist and the codirector of the BrightMind Labs, we came up with a set of design principles that can be applied to any game to make it suitable for ADHD children, especially with the aim of increasing their self-esteem as a result of playing the game. We refer to our design approach as *BRIGHT* (the letters are taken from the keywords for this project).

There have been some studies on health-related games mainly for encouraging physical activities, stroke rehabilitation and diabetes, brain training, ADHD diagnosis and helping ADHD-diagnosed children solve social problems [9–16], but we are not aware of any game designs targeted specifically for improving self-esteem in children with ADHD.

This paper presents the steps towards the development of our proposed game design with a particular focus on improving self-esteem. It then follows by discussion of how these principles were applied to an open-source Android-based mobile game. A preliminary evaluation of the game will also be reported. We believe that our research paves the way for the systematic design and development of fully fledged computer games dedicated to improving self-esteem in children with ADHD.

6.2 *BRIGHT* Design Approach

According to Kirriemuir [17], there are two key themes common to the development of games for education: (1) the desire to harness the motivational power of games in order to "make learning fun" and (2) a belief that "learning through doing" in the form of games offers a powerful learning experience. The first theme is broadly criticised in the literature. As pointed out by Rieber et al. [18], games should not be treated simply as educational "sugar coating", making the hard work of learning easier to "swallow". Instead, we have to consider both the motivational and cognitive power of games [19].

The real educational value of a computer game should be exemplified by its ability to create a playful learning experience for children through experimentation, progressive exploration, trial and error, and imagination. Therefore, a game designed to satisfy these criteria might stand for an ideal platform for education and cognitive development. It is, therefore, clear that learning through a computer game should be purposely structured through a series of exploration tasks so that children can discover essential skills in a progressive and experimental manner. This leads to our main research question: How can we improve self-esteem in children with ADHD through playing computer games?

To address this research question, the nature of computer games needs to be carefully examined. The key concept that is frequently utilised to explain the level of engagement in a computer game is that of "flow", first introduced by Csikszentmihalyi [20]. Many researchers consider flow as the state of intensive involvement. It is widely believed that flow is the key to the success of an educational game [21]. According to Malone [22], several conditions are likely to induce the flow state. Among them, a few conditions are of particular importance for designing educational games:

- C1 The activities in a game should be structured so that the level of difficulty of the game can be adjusted to match children's knowledge.
- C2 The activities in a game should provide concrete feedback to children so that they can tell how well they perform and perhaps what they need to do to perform better. In particular, the performance of the game should be closely related to children's current state of knowledge of the domain.
- C3 The activities in a game should present a variety of challenges such that children can obtain increasingly complex information about different aspects of domain they are learning.

It can be argued based on Malone's conditions that instead of aiming for a gaming experience that superficially conceals the educational purpose behind fun activities, a careful design of the structure of the game is highly desirable. Specifically, the game structure should contribute to the flow and subsequently the creation of an active learning and visually stimulating environment.

Among all types of games, it appears that simulation and role-play games are most likely to satisfy these requirements. In fact, learning through direct experience, which is enabled by simulation and role-play, has been consistently demonstrated to be more effective and enjoyable than learning through information communicated as facts. Although simulation and role-play games may be suitable, we argue that other types of games can, when designed according to sound principles, lead to a positive outcome for children with ADHD symptoms.

Based on what we found in the ADHD literature, our earlier work in this area [23] and our experience in dealing with such children, we present *BRIGHT*—a set of generic design principles aimed to increase self-esteem in ADHD children as a result of playing computer games:

- Positive feedback (PF): Provide constant positive feedback and recognise the effort, when the player is doing a good job and is gaining new scores—this is particularly important for improving self-esteem.
- Clear instructions (CIs): Give them clear instructions from the beginning as to what they are required to do.
- Specific goals (SGs): Give them specific goals, e.g. to achieve a certain score in order to finish a specific level.
- Encourage them to think straight (TS): Our aim here is to encourage the players to slow down, analyse the situation and create a strategy rather than rushing to reach the final goal. Children with ADHD are usually impatient [2, 4, 7], and because of the hyperactivity, they are always rushing. TS design principle focuses on improving this behaviour.
- Encourage them to organise themselves (OG): The objective here is to help the players create the habit of planning ahead. We believe that this is effective, as the majority of children with ADHD are disorganised [7] and planning ahead helps them address this issue.

To evaluate the proposed design empirically, we had to identify an appropriate game and modify it using the proposed design strategies discussed earlier. Guided by Malone's conditions, efforts were made to compare and select suitable games as the basis for our quest towards tackling the research question. Many open-source games were studied, and GLtron (http://en.wikipedia.org/wiki/GLtron) was finally selected. The game consists of controlling a motorcycle on a large and limited square area by turning it to the left or to the right. During the motorcycle movement, each player creates a wall following its path and this wall blocks the way of other players on the scene. The goal of the game is to be the last player riding. Cycles can be boosted with a limited turbo. There are various gameplay styles, including switching the gameplay from "booster" to "wall accel." to "both". "Booster" has an extra button for boosting, in addition to the standard left, standard right, glance left, glance right buttons, while "wall ride" increases a player's light cycle's speed automatically depending on how close they are to an opponent's wall. "Both" incorporates both options for increasing the player's light cycle's speed. There are several arena sizes that can be selected, from "tiny" (which is best for two players on normal speed) to "vast".

GLtron is an action-packed game with good visualisations and enjoys a good match with Malone's conditions: the level of difficulty of the game can be adjusted

Fig. 6.1 Modified version of GLtron for mobile devices

(C1), feedback is constantly provided to show players how well they are doing (C2), and the game becomes more challenging as they keep playing (C3). We felt that it would be an engaging and fast-moving game for children and a good fit to start off with. The game is released under the GNU General Public License.

The changes were made to the mobile (Android) version of GLtron as a proof of concept. Screenshots of the modified game are shown in Fig. 6.1 along with a positive feedback message on the second screen shown to the player.

6.3 Applying *BRIGHT* Approach to GLtron

Driven by the five design strategies, namely PF, CI, SG, TS and OG, modifications were made to the GLtron game (see Fig. 6.1). At the beginning of the game, the instructions are clearly explained (following CI principle). The player would be given a clear goal—that is to be the last one riding if they want to win the game (SG). The number of players is shown on the screen at all times. The game will gradually become more challenging in the following ways, if they win in less than *t*(s) seconds:

1. The number of artificial players will automatically increase, and the updated number gets displayed on the screen.
2. The speed will also increase, and an updated speed will be shown to the player.

The players are encouraged to think of a new strategy as the game gets more challenging (TS & OG). Positive feedback in various formats is constantly provided when the player has achieved something and a difficult obstacle is overcome (PF). We believe that this will directly affect their self-esteem. Some of the example feedback messages given in different scenarios are as follows:

- Every 15 s give them one of these messages (picked randomly):
    - *Well done* !
    - *Keep up the attention, <<player's name>>* !!

    - *Good focus, <<player's name>>* !!
    - *keep going* !!
    - *Nearly there* !
    - *Well done at keeping alert, <<player's name>>* !!
    - *Great job* !

- Every time another car crashes:
    - *Well done* !
    - *keep up the attention, <<player's name>>* !!
    - *Good focus <<player's name>>* !!
    - *Well done at keeping alert, <<player's name>>* !!
- After every 15 min of playing, if they have won at least once, give them this message:
    - *Well done <<player's name>>, very good focus! Show this to your teacher*!
- Each time they win, change the default message of "you won" to:
    - *Well done <<player's name>>, you won! You have a very good focus.*

The modifications made aim to show ADHD-diagnosed children that they can achieve their goal, when they are focused. To find out how and for how long they interact with the game, children need to login with their username in order to play the *BRIGHT* version of the game. Many game-playing activities, such as player's name, start and finish time and date, score, speed, change in speed, level size, number of players, change in number of players, number and type of messages they get on the screen, each time they win or lose, and length of play, will be logged on the tablets in addition to timestamp for each entry. The log will help us to find out whether children's self-confidence will improve after playing the game for some time.

6.4 Preliminary Evaluation

We carried out a pilot study with the *BRIGHT* version of GLtron in March 2015. Thirty-six users (17 males and 19 females, aged 20–29) took part in our study by playing the game for 30 min and filling out a user questionnaire at the end. The results are shown in Table 6.1.

Overall, the game was well received. 81 % of participants believed that the game has merit in increasing confidence in children who have low self-esteem. 79 % thought our version of GLtron kept players motivated, and 76 % (of those who had played the original version) said that they would spend more time playing the modified version of the game and/or would allow their children to spend more time playing it compared with the original version. We received very positive comments, for example: "*I believe the game can help children concentrate*", "*innovative*

Table 6.1 Subjective evaluation

Question	Yes, very easy or high merit (%)	Yes, easy or some merit (%)	Neither yes nor no (%)	No, difficult or little merit (%)
Were the game controls easy to use?	58	26	12	4
Did you have fun playing the game?	51	29	13	7
Do you think the game has merit in increasing children's self-esteem?	66	15	14	5
Did you get well through a challenge?	34	29	21	16
Were the messages given to you, while you were playing, made you focused more in winning the game?	31	42	27	0.00

approach", "*I can see a lot of potential in improving one's confidence*" and "*enjoyed playing it*". Some suggestions were also made for further improvement. Some users asked us to award them using points in the game in addition to providing positive feedback during the session. One user thought that it might be a bit too challenging for younger children to win and another one suggested some of the feedback messages to be shortened, as they might influence the player's experience otherwise. A user asked for more improvement in visual effects and sounds and a few others asked for it to be personalised to the players, as some are more experienced than others.

6.5 Conclusions and Future Work

In this paper, we presented the initial steps towards development of *BRIGHT*, a novel game design for increasing self-esteem in children with ADHD. We applied the design to GLtron, an open-source mobile game, and presented the results of an initial pilot study. The results showed that the players liked the idea, enjoyed playing the game and believed that it adds value.

We plan to address the feedback received from the initial study and evaluate the effectiveness of the proposed design on mobile platforms with ADHD-diagnosed children aged between 6 and 11. Three acceptance indicators will be measured: the increase in self-confidence as a result of playing, engagement with the game and the player's enjoyment. These will be measured during and after playing the original and *BRIGHT* versions of the games for a week. We hypothesise that the *BRIGHT* version will increase their self-esteem, engagement with the game and enjoyment. Considering Gardner's seven types of intelligence [24], making *BRIGHT* games personalised to the players' skills will be our next goal. We aim to present players with different challenges, e.g. linguistic, mathematical, spatial, kinesthetic, musical, interpersonal and intrapersonal, to find out which type(s) of intelligence they belong to and what their preferred way of learning is. The information gathered in this phase of the project should also help parents and educators develop children in areas they are good at. We also plan to conduct a longitudinal user study for a period of 3–6 months to examine whether using *BRIGHT* games can lead to long-term behavioural changes. We believe that our research paves the way for the systematic design and development of full-fledged computer games dedicated to improving self-esteem in children with ADHD.

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Chapter 7
Smart Classroom 2.0 for the Next Generation of Science Learning in Taiwan

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Abstract This paper provides an overview of how National Taiwan Normal University is taking its endeavor to renovate the current science learning environment by establishing a Smart Classroom 2.0 (SC 2.0) using innovative information and communication technology and by utilizing mobile-assisted technology in science learning. A baseline study was conducted to survey students' general preferences of various SC 2.0 systems. The results revealed students' suggestions on several SC 2.0 systems to meet their learning needs. Among which, two systems, namely the speech-driven PPT and the technology-enabled interaction system, have been developed and pilot tested. The pilot test results indicated that students' general perceptions toward the two systems in facilitating their learning are fairly positive. Having experienced both systems, students, in particular, showed significant improvements in how they viewed learning with the use of ICT. Students' self-perceived learning motivation and effectiveness have improved significantly. In addition to the use of innovative ICT in science learning environment, the university has further extended its efforts to utilize mobile devices into pre-service teacher education. Ultimately, we anticipate that our SC 2.0 systems can be integrated into mobile devices in order to help teachers to better facilitate students' learning.

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Keywords Information and Communication Technology · Smart Classroom · Speech-Driven PowerPoint · Technology-Enabled Interaction System · Teaching and Learning

7.1 Introduction

The term "smart classroom" generally refers to a traditional classroom incorporated with multi-technology and media systems to make the classroom environment sensitive to meet the teaching and learning needs [1]. Other similar terms that have also been used to describe this kind of modernized classrooms include the following: "eStation," "intelligent classroom," "smart space," "ambient intelligence," and the like. A typical smart classroom usually consists of diverse functions highlighted to support various classroom activity needs. Different information and communication technologies (ICT) were used in the related studies to support those functions and needs, for example, web-based technologies, wireless and mobile technologies, digital whiteboard technologies, audio and video recognition technologies, and face and gesture recognition technologies [1–4]. As Taiwan responds to the growing pervasiveness of ICT, many universities are taking the endeavor to establish a technology-integrated smart classroom with the anticipation to increase instructional effectiveness. National Taiwan Normal University (NTNU) is also taking its efforts to renovate the current science learning environment by constructing a Smart Classroom 2.0 (SC 2.0) at college level using innovative ICT and by utilizing mobile-assisted technologies in science learning [1]. The ultimate goal of this research is to offer practical knowledge and experience to inform school teachers, educational researchers, and computer engineers to better integrate technologies in classroom environments.

7.2 Methods

7.2.1 Smart Classroom 2.0 Systems

NTNU has taken the initiative to renovate the current science learning environment by constructing a SC 2.0 at college level, which consists of various innovative systems. Among which, this study will only explore the impacts that two of the SC 2.0 systems, SD_PPT and TEIS, have on teaching and learning.

Speech-Driven PowerPoint (SD_PPT). This system involves the speech recognition technology to identify certain keywords as they were spoken and to respond automatically by presenting the corresponding slides. Traditionally, when this lesson was taught, the instructor would raise simple questions to help students' brainstorm ideas and have better engagement in the class. Based on students' answers, the instructor would show the corresponding slides on the PowerPoint to help them visualize and comprehend more easily. However, since the instructor had no way of predicting the sequence of students' answers before hand as he organized the PowerPoint slides, based on students' answers each time, he would need to quickly browse through the entire PowerPoint in order to find the desired slides. Though the instructor's intention was to improve students' engagement in class, there existed the trade-off of interrupting the flow of the class. Therefore, the SD_PPT system was developed with a purpose to not only free the instructor from the teaching platform, to save time from browsing through the slides, but also to increase students' attention in class and to promote teacher–student interactions.

Technology-Enabled Interaction System (TEIS). This system involves the face recognition technology to automatically recognize students in the classrooms. This system requires the students be photographed prior to attending the class. Through the use of cameras and laptop computers during the class, students' video images are captured, analyzed, and transmitted real time to the instructor's laptop at the platform. Students' names and their seating can be shown to the instructor at once. The instructor will then have the idea of who is in the class without taking the attendance. In addition, the system can enhance teacher–student interaction by allowing teachers to be on the first-name basis with all the students from day one.

7.2.2 Participants and Procedures

Both systems of SD_PPT and TEIS were deployed and tested to an elective earth science course. Approximately 15 undergraduate students, 5 males and 10 females, participated in the study. Students were pretested a week prior to the testing for their general perceptions on incorporating ICT in their classroom learning. During class time, the instructor gave a lecture to students about the distinctive characteristics of various dinosaurs and helped students distinguish between the facts and the fallacies about dinosaurs from the movie clip of *Jurassic Park*. The instructor pre-designed a lesson with the systems of SD_PPT and TEIS, which were then deployed during the lecture time. Upon completion of the lecture, a posttest was administered. In addition, student reflections and teacher interviews were held to explore whether their teaching and learning were affected when using the systems.

7.2.3 Instrumentation

A 15-item questionnaire, namely Attitudes toward ICT-Supported Learning (AICT-SL), was administered in this study. The questionnaire used five-point Likert-type scale ranging from 1, strongly disagree, to 5, strongly agree. The rotated solution using varimax rotation revealed the presence of four factors, which together explained a total of 76.8 % of the variance. In particular, factor 1 (learning motivation with ICT, LM_ICT) contributed 28.8 %; factor 2 (learning effectiveness with ICT, LE_ICT), 18.9 %; factor 3 (SD_PPT), 16.9 %; and factor 4 (TEIS), 12.3 % of the variance. The reliability of AICT-SL was 0.83.

7.3 Results and Discussions

The results shown in Table 7.1 indicated that having experienced the systems of SD_PPT and TEIS, students' overall attitudes on ICT-supported learning improved significantly from 3.66 to 4.05 ($t = -2.71$, $p = 0.017$, $d = 0.70$, medium effect size). Though neither the breakdown results of SD_PPT nor the TEIS reached statistical significance ($p = 0.164$ and 0.294, respectively), both systems reached small effect sizes ($d = 0.38$ and 0.28, respectively). Note that researcher has suggested the greater possibilities of achieving a statistical significance when the sample size is large [5]. With the small sample size in this study, it is therefore more likely to obtain a statistically insignificant result. However, significant effect sizes in this study may still serve as practical indicators for possibilities of achieving statistical significance in future replicated studies with larger sample sizes. Due to the small sample size of this study, the statistical significance level was set at $\alpha = 0.1$.

7.3.1 Speech-Driven PowerPoint (SD_PPT)

Higher Student Engagement and Greater Teaching and Learning Efficiency. Students' survey responses for SD_PPT suggested that their average level of agreement increased significantly from 4.13 to 4.33 toward the statement "*I feel I have more interaction with the instructor when our answers to the teacher's questions can activate the PPT to illustrate the corresponding images or information*" ($t = -1.87$; $p = 0.082$; $d = 0.48$, approaching medium effect size). As students generally pointed out in their reflections, not only their "*incentives for*

Table 7.1 Results of students' general perceptions toward ICT-supported learning

Scales	Pretest M(SD)	Posttest M(SD)	t	p	d
Overall attitudes on ICT-SL	3.66(0.48)	4.05(0.53)	−2.71	0.017^{**}	0.70
SD_PPT	4.03(0.47)	4.23(0.50)	−1.47	0.164^{a}	0.38
TEIS	3.97(0.42)	4.12(0.52)	−1.09	0.294	0.28
LfM_ICT	3.24(1.30)	3.98(0.69)	−2.16	0.049^{**}	0.56
LE_ICT	3.63(0.49)	3.93(0.75)	−2.08	0.056^{*}	0.54

Note: $^{*}p < 0.1$; $^{**}p < 0.05$
[a]Marginal significance

learning" have increased, but they have become "*more focused*" and "*paid more attention*" in the class. They also liked the fact that their "*interaction with the teacher is enhanced through SD_PPT.*" Many others also indicated that the system helped them by "*deepening memory and making learning more efficient.*" This echoed with the survey result that students' attitudes toward the statement "*I feel my learning is more efficient as my teacher or classmates speak of certain keywords, the PPT will automatically illustrate the corresponding images or information*" improved from 4.00 to 4.20 ($t = -1.15$, $p = 0.271$, $d = 0.30$).

Likewise, the instructor indicated during his interview that, "*the SD_PPT system allows not only myself but also the students to interact with the course contents, which ultimately increases students' in class participations*." The teacher also indicated that since his teaching style "*involves a great deal of moving around in the classroom*," this system can indeed meet his teaching needs by unrestricting him from the teaching platform and enabling him to interact with the system and the students at the same time. He also noticed "*an increase in students' attention in class when the SD_PPT system was used as opposed to the regular PPT.*"

Lack of System Stability May Cause Unexpected Classroom Interruptions. In spite of the many positive feedbacks, since the system is still in its preliminary stage of development in education, the accuracy of voice recognition still needs room for improvements. Some students indicated that "*when the PPT did not react to the prompt or retrieved the wrong slides, it caused interruptions in the class.*" Students suggested that their "*learning would be much more effective if the accuracy of the system can be enhanced.*" Similarly, the teacher expressed that to adapt to the still yet unstable system, he had to consciously slow down the pace of his speaking and spoke with extra clarity which may cause extra pressure and anxiety in his teaching.

7.3.2 Technology-Enabled Interaction System (TEIS)

Reinforcement for Students' Class Participation. Several students expressed their satisfaction with the system when they were recognized by the teacher in the first-name basis. As one of them stated that "*it feels better to be called by name rather than by the color of my clothes*." Some students indicated that through the TEIS, their class attendances have increased and that they were "*less likely to doze off in the class*." Others revealed that they "*concentrated more in the class*" when the system was used. The student feedbacks from the survey also paralleled with their reflections that having experienced the system, their level of agreement to the statement "*if the teacher can know me by my name in the class, it will help me pay more attention in the class*" significantly increased from 3.27 to 4.07 ($t = -2.10$; $p = 0.054$; $d = 0.54$). In addition, the instructor also pointed out in the interview that the TEIS system helped him "*memorize students' names easier than the traditional attendance sheet*" so that he could "*interact with the students more easily*."

Restrictions for Learning and Teaching. Aside from the positive feedbacks, one student reacted negatively stating "*it is uncomfortable to be watched*." Another one indicated "*what a pressure it is that the teacher can be perfectly aware of who I am and what I'm doing in the class…it is odd to be known* via *a machine*." The instructor also pointed out a drawback of the system that his teaching was somewhat restricted by the monitor of TEIS mounted at the teaching platform. He suggested if the system can be further developed to transfer all the information from the monitor to his smart phone, then he can "*move more freely and have more interaction with the students*."

7.3.3 Information and Communication Technology (ICT)

Higher Learning Incentives and Learning Effectiveness through ICT-Supported Learning. As shown in Table 7.1, students' perceptions toward learning motivation with ICT (LM_ICT) improved substantially from 3.24 to 3.98 after the lecture ($t = -2.16$; $p = 0.049$; $d = 0.56$, medium effect size). In their reflections, students indicated that "*learning becomes more fun*" and their "*learning interests have greatly increased*" in an ICT-supported learning environment. Likewise, having experimented with both systems, students' self-reported perceptions toward learning effectiveness with ICT (LE_ICT) have also increased from 3.63 to 3.93 ($t = -2.08$; $p = 0.056$; $d = 0.54$, medium effect size). When students rated their "*preference to have classroom activities which integrate ICT into learning processes*," their average rating has significantly increased from 3.13 to 3.80 ($t = -2.00$; $p = 0.065$; $d = 0.52$, medium effect size).

In general, both teacher and students perceived positively toward the SD_PPT and TEIS systems. Students' perceptions toward learning in an ICT-supported learning environment have also significantly improved after experiencing both systems. However, since the systems deployed in this study are still in early stage of development, more system stability is anticipated to better facilitate their learning. In continuation of the SC 2.0 system developments, we have integrated all the SC 2.0 systems in mobile devices and implemented mobile-assisted teaching in a teacher preparation class. With this, we hope that pre-service teachers can have the convenience of utilizing innovative systems into their teaching, and their capabilities in mobile-assisted teaching can be fostered. However, while integrating innovative technologies into classrooms, it is essential to focus on the instructional and learning needs in order to develop a SC 2.0 and/or mobile-assisted learning environment that can truly help enhance teaching and learning as a whole.

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Chapter 8
Software-Defined Networking (SDN)-Based Network Services for Smart Learning Environment

Kannan Govindarajan, Vivekanandan Suresh Kumar, David Boulanger, Jérémie Seanosky, Jason Bell, Colin Pinnell, Kinshuk and Thamarai Selvi Somasundaram

Abstract This research paper introduces a state of the art for coupling software-defined networking (SDN) capability in smart learning environment (SLE). Smart Competence LEarning Analytics platform (SCALE) is the learning analytics platform, which has been developed to analyze and measure the learners data (Big data) generated in SLE for understanding the various learners competence measures. The learning analytics involves various processes such as distributing, analyzing, and merging the results across the clusters. It requires a large amount of bandwidth and computation cycles in an on-demand manner to reduce the total computation time and computation cost. Hence, in this research paper, we introduce a SDN-based networking principle with SCALE, which provision the network paths and allocates the bandwidth in an on-demand manner. The experiment results were conducted to analyze the performance and impact of SDN in SCALE platform.

Keywords Smart learning environment · Big data · Learning analytics · Smart Competence LEarning Analytics platform · Software-defined networking · OpenFlow · Computation time · Computation cost

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8.1 Introduction

Smart learning environment (SLE) [1] is a powerful learning tool that provides on-demand and adaptive support to the learners based on the analysis of their learners needs. In recent years, it has became more popular and a large number of learners, academic institutions, and industries started to use across the worldwide that generates large amount of learners' data. Smart Competence LEarning Analytics platform (SCALE) [2] is an in-house learning analytics platform designed and developed to track the fine-level learning experiences and translates those experiences into opportunities for customized feedback, reflection, and regulation. It has witnessed that, it has to deal with a large amount of learners data also known as Big data. Hence, it is essential to extract, process, and analyze those learners data in a rapid and an efficient manner to understand the learners various competence measures. Ku [3] analyzed the problems in conventional e-learning environment and stated that "smart learning is not just providing e-learning services through mobile devices, it should have an intelligent customized learning services optimized for the learners' on a personalized mobile device." Map Reduce [4] and Dryad [5] are the most popular distributed processing frameworks used in the market to process the Big data. These frameworks split the Big data and distribute those data in parallel across the Hadoop [6] clusters to analyze, transfer, and merge the results. The Big data processing requires vast amount of computation cycles and bandwidth across the clusters and between the analytics engine and the clusters in on-demand manner.

However, SCALE is currently using the conventional networking principle of subscription-based method. Conversely, the main drawback in the conventional networking is allocation of bandwidth in an on-demand manner that requires lots of manual intervention and time-consuming process and involves more laboring cost that increases the total computation time and computation cost. Hence, in this research paper, we propose to marry the software-defined networking (SDN)-based [7] networking principle with SCALE platform, which will create the network paths, inject the flows, and allocate the bandwidth based on the demand. OpenFlow [8] protocol is used to establish the communication between the networking devices. The research works [9–11] have investigated the advantages of SDN for Big data application processing to reduce the processing time, dynamically creating network paths, etc. The article discussed [12] the capability of SDN to build a large, intelligent network that is capable to handle both structured and unstructured data as part of Big data analytics, and it eliminated the pain of manual administration, which exists in the conventional networking resources. In summary, the main contributions of research work are summarized below:

(A) Designing a SDN-based network services for SCALE platform for performing learning analytics in a Smart Learning Environment.
(B) Provisioning of network paths, injecting flows, and allocating the bandwidth in a dynamic manner for reducing the total computation time and total computation cost.

(C) Creating a SDN-based Hadoop infrastructure with OpenFlow switches and OpenFlow protocols.
(D) Analyzing the impact of SDN-based networking services in the SCALE platform.

The rest of this paper is organized as follows: Sect. 8.2 describes the research works, which are closely related and provides background knowledge to support our research work. Section 8.3 discusses the problem statement and the proposed solution to solve the problem. Section 8.4 describes the system architecture for implementing the proposed work. Section 8.5 discusses the performance measures of the proposed system. Section 8.6 concludes the paper with recommendations and future work to be explored further.

8.2 Related Works

Ku [3] analyzed the base technologies for the SLE and examined the problems in conventional e-learning environment. The study has concluded that, it is essential to include context aware technology, Big data technology, and cloud computing in traditional e-learning services to build a SLE. Das et al. [10] proposed a network management framework named FlowComb, which is helpful for Big data application processing to achieve high utilization and low data processing times. Their proposed system is capable to predict the application transfer time based on the software agents installed on application servers. Their experimental results are evident that their proposed system reduces the Big data processing time in a remarkable manner. Benson et al. [13] proposed a framework named as Cloud Networking as a Service (CloudNaaS). It extends the self-provisioning model of providing network devices in an on-demand manner in addition to compute and store devices. Mahenge and Mwangoka [14] designed a cost-effective mobile-based content delivery system to deliver the contents in a resource and bandwidth constraint environment. They claimed that the proposed system has the potential to reduce the bandwidth cost, the server workload, and the Internet usage overhead. They improved the quality of experience and learners' participation using their proposed system.

8.3 Problem Statement and Solution

SCALE requires a large amount of computation cycles and network bandwidth to process and analyze the collected data in an on-demand manner. Figure 8.1 represents the working mode of SCALE using the conventional networking structure. Figure 8.2 represents the schematic representation of the solution to solve the above-said problem.

SCALE communicates with SDN controller through SDN connector to initiate learners data analytics process. The controller node and cluster nodes should be

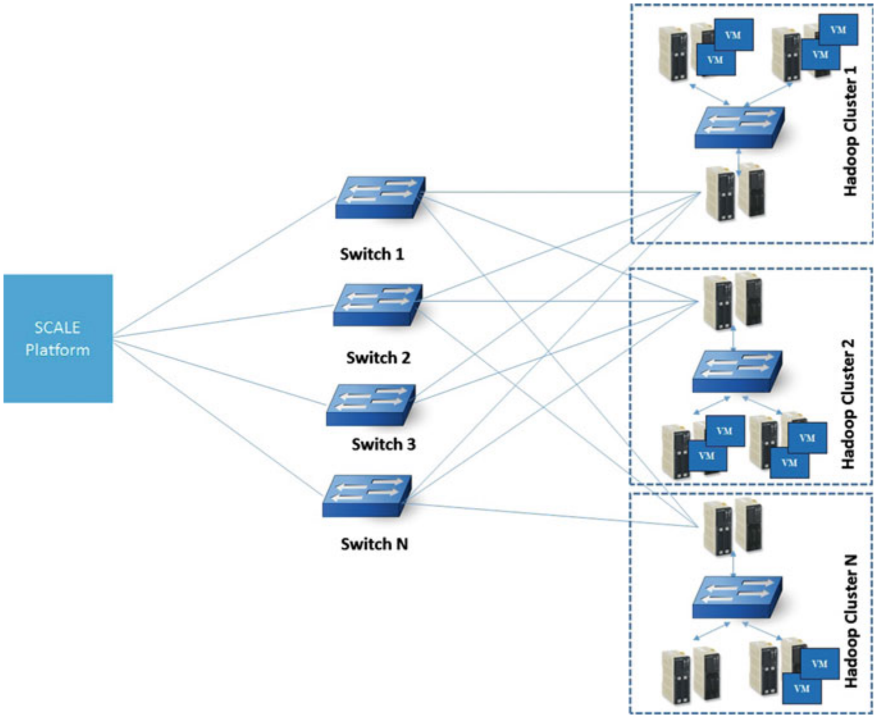

Fig. 8.1 Problem representation

configured with Open vSwitch (OVS) [15] software that can act as the physical switch, as well as the virtual switch. The queues (Q1–QN) are created in OVS and each queue is assigned with a specific bandwidth value. The virtual network V1 and V2 has been created, and it is allocated with a link bandwidth value of B1 and B2, respectively; it can be modified dynamically based on the demand.

8.4 Proposed System Architecture

The system architecture for implementing the proposed research work is shown in Fig. 8.3.

The data collector module collects the learners' data from Moodle, MI-LATTE, CODEX, and Hackystat sensors that consists of both structured and unstructured data. It stores the data in Hadoop Distributed File System (HDFS) clusters through data storage manager. The SDN connector acts as the interface between the OpenFlow switches and SCALE platform using the OpenFlow protocol. The data preprocessor periodically queries, fetches and, preprocesses the learners' data that remove the unwanted fields, name, and id of the learners for privacy purpose.

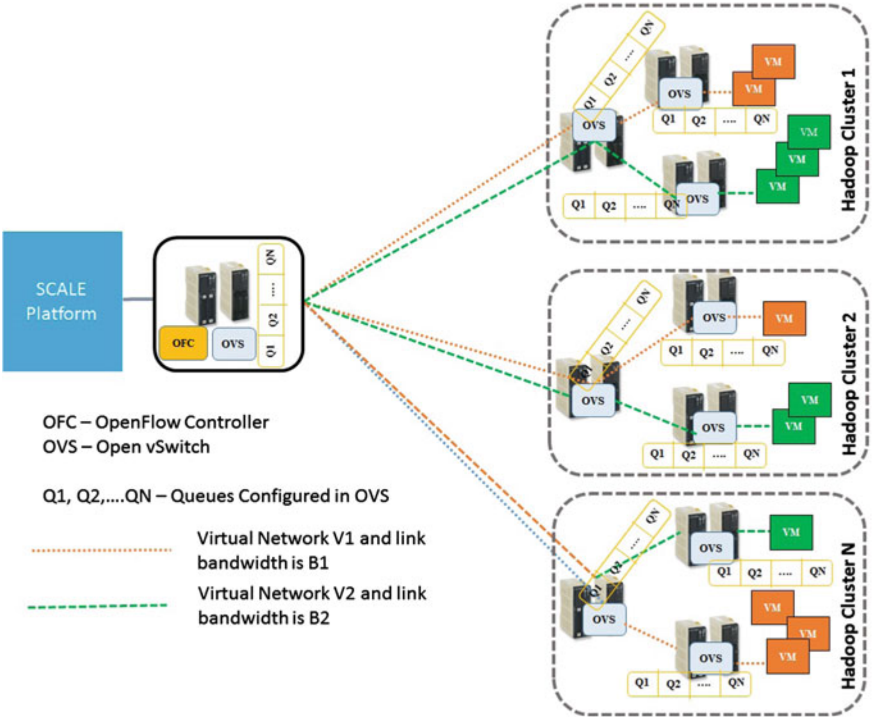

Fig. 8.2 Schematic representation of solution

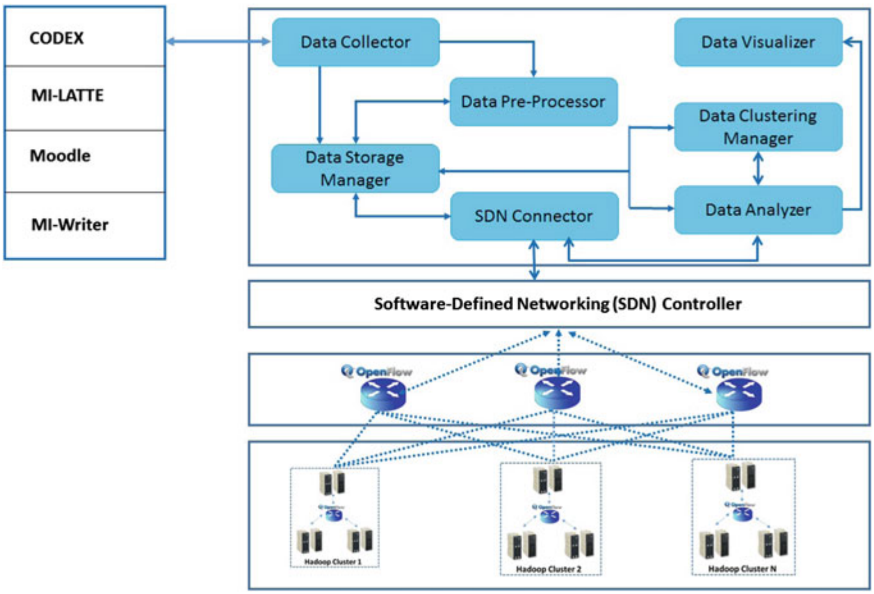

Fig. 8.3 System architecture

The preprocessed data are sent to the data clustering manager which is embedded with the particle swarm optimization (PSO) [16] clustering algorithm. It group the similar learners in an optimal manner based on the learners efficiency, quality, and accuracy. The data analyzer component is integrated with various machine learning and statistical algorithms that initiates the learning analytics process across the Hadoop clusters. The SDN controller provisions the network paths in the OpenFlow switches in a dynamic manner and allocates the required bandwidth to network links in each cluster by injecting the flows for performing learning analytics process. Finally, the analyzed learners' data are fed into the data visualizer to visualize the various competence measures in terms of graphical charts and statistical values.

8.5 Performance Measures

The performance of a SDN-based learning analytics platform is determined by analysis of total computation time and computation cost, which is calculated using Eqs. (8.1) and (8.2). To perform this experiment, we have generated the learners data, which is based on the traces of real-time learners data. The data size ranges from 2 to 32 GB and the OpenFlow switches are configured with a maximum date rate of 200 Mbps. For the first experiment (without SDN), a single queue is created and allocated a bandwidth value of 100 Mbps. The second experiment (with SDN) is conducted by creating multiple queues, which ranges from Q0 to Q4 and bandwidth is allocated in the range of 20–100 Mbps. The proposed work allocates the bandwidth to the learning analytics process of various data sizes in an on-demand manner based on the required bandwidth in SCALE platform. Figures 8.4 and 8.5 represent the total computation time and total computation cost to perform the learning analytics process for the collected learners data. The total computation time (TC_{Time}) is calculated using Eq. (8.1). It is the summation of task distribution time (TD_{Time}), data analyzing time (DA_{Time}), results merging time

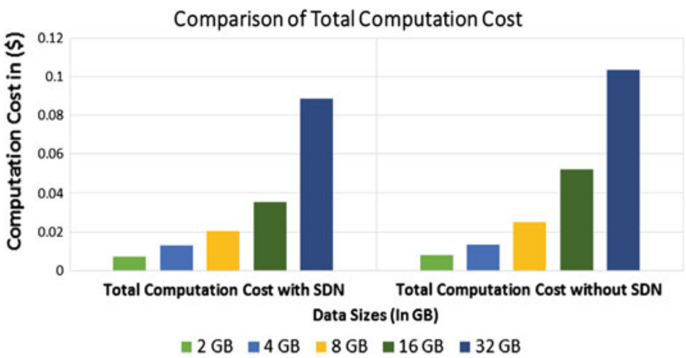

Fig. 8.4 Comparison of total computation time

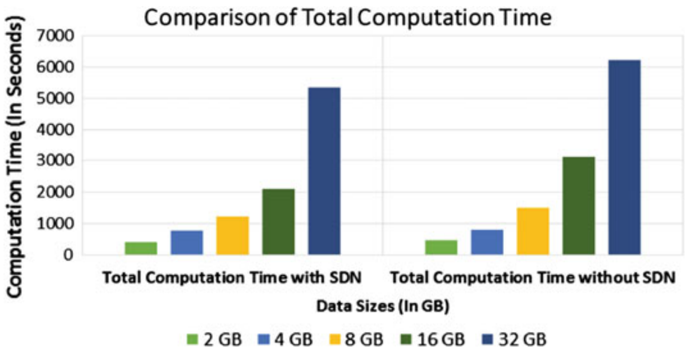

Fig. 8.5 Comparison of total computation cost

(RM_{Time}), and data transfer time (DT_{Time}). The total computation cost (T_{Cost}) is calculated using the Eq. (8.2), which is based on the usage of bandwidth value for the learning analytics process of various data sizes.

$$TC_{Time} = TD_{Time} + DA_{Time} + RM_{Time} + DT_{Time} \tag{8.1}$$

$$TC_{Cost} = (TD_{Time} + RM_{Time} + DT_{Time}) * BW\_Usage * \$/h \tag{8.2}$$

8.6 Discussion and Recommendation

SLE is capable of providing an on-demand and adaptive support for the learners based on their needs. SCALE is the learning analytics platform to analyze and understand the learners competence measures that requires a huge amount of computation cycles and bandwidth in an on-demand manner. In this research paper, we have investigated the effect of coupling SDN-based networking principle in learning analytics process. From this study and the experimental results, the following things have been identified and recommended as follows:

- The SLE generates a huge volume of learners' data known as Big data. The total computation time required to process those data are high that increase the total computation cost.
- The conventional networking is unsuccessful for provisioning of bandwidth in an on-demand manner due to various limitations. However, SDN has the capability to provision the network paths, allocating the bandwidth to the provisioned network paths in an on-demand manner.
- The SDN-based network services in Smart Competence LEarning Analytics (SCALE) platform reduces the total computation time and computation cost of learning analytics process.

The future work intends to extend this research study further: (i) to develop an intelligent scheduling mechanism to identify the suitable computation and network nodes that increase the efficiency of learning analytics process. (ii) to extend the SDN-based SCALE platform for video streaming of online lectures and improving the Quality of service.

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Chapter 9
Design of Theoretical Model for Smart Learning

Xiaolin Liu, Ronghuai Huang and Ting-Wen Chang

Abstract Smart learning is the learning activity which can enable high learning experiences, high content suitability, and high learning efficient. The research on smart learning and smart learning environment (SLE) is just at the very beginning. There has not been a mature research framework on smart learning. Thus, this paper proposes a theoretical model for smart learning, aiming to provide a research framework for smart learning. This theoretical model is composed of supportive SLE and smart learning cycle. SLE is an open-ended, intelligent, and integrated learning space based theoretically on constructivist learning theory, blended learning theory, and modern education methods, which is composed of the corresponding devices, tools, techniques, media, teaching resources, teacher communities, and learner communities. The smart learning cycle includes three factors of learner: metal system, learning behaviors, and outcomes. These three factors are connected by four types of interactions: the plan of smart learning from learner's mental system; the execution, monitoring, and evaluation of learning behaviors; the feedback from learning outcomes to learning behaviors; and the feedback from learning outcomes to mental system. This model could provide a framework for the further studies which aim at building an effective SLE by considering different features and factors of smart learning.

Keywords Theoretical model · Smart learning · Smart learning cycle · Smart learning environment

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9.1 Introduction

Technology is continuously transforming the way we live and work. The effect of information and communication technology (ICT) plays on reshaping education progressively appears. The way that ICT integrated into classroom has shifted from the initial peripheral participation in supporting the traditional teaching to the present key enabling factor that reshapes teaching and learning [1]. Bates [1] points out that technology reshapes learning from trends of online learning, blended and hybrid learning, open learning, and MOOCs. Actually, with the ICT infusing in education, it not only enriches the form of teaching and learning, but also radically transforms the requirement for talent who should have skills of global awareness, communication and collaboration, critical thinking and problem solving, social and cross-cultural skills, and self-direction and interactive. Namely, learning is understood more than merely the grasp of knowledge but cognitive skills, interpersonal skills, intrapersonal skills, and consideration [2], which calls for the radical reshaping of teaching and learning in the twenty-first century. However, a profound gap exists between the knowledge and skills most students learn in school and the knowledge and skills they need for success in the twenty-first century.

In order to prepare students with twenty-first-century skills in smart learning environment (SLE), we should firstly know what smart learning is like. Thus, a theoretical model for smart learning is critically needed. The paper first inspects the current study of smart learning and clarifies features of smart learning, on the basis of which the paper build a theoretical model for smart learning, aiming to provide a basis for the further study on smart learning.

9.2 Smart Learning and Smart Learning Environment

In 2008, IBM announced its smarter planet campaign, which aims to build a smarter planet of more instrumented, intelligent, and interconnected [3]. IBM kicks off a new era of "smart+" across all types of enterprises from "smart city," "smart transportation," "smart medical treatment" to "smart food." In response to the "smarter planet," researchers in education also coined the terms "smart education," "smart educational environment," and "smart learning." In the following of this section, features of smart learning and SLE are presented, and the theoretical foundations of the model to be constructed are clarified.

9.2.1 Features

The research on smart learning and SLE is just at the very beginning. There has not been a mature research framework on smart education, though some researchers have started to explore some basic issues on smart learning and SLE. Some researcher defines smart learning as the learning mechanism that utilizes smart devices, along with cutting-edge ICT for education which emphasizes the devices used in learning are intelligent [4]. Smart learning is the learning activity which can enable high learning experiences, high content suitability, and high learning efficient [5]. It can also utilize modern scientific technology to provide students, teachers, and parents with a series of supportive and on-demand services. In addition, it can overall collect and apply data from both participants' status and teaching process to promote equity, continuous improvement of performance, and to cultivate excellence of learners.

The features of smart learning are concluded as sensible, adaptable, and caring [4]. Sensible refers to the state that various technologies (such as GPS, RFID, and QRCode), sensors (such as sensors for temperature, humidity, carbon dioxide, and illumination), and questionnaires are used to sense the environment indicators around learners and the learning features of them. Adaptable describes the condition that both the learning resources and the learning activities are on the individual's learning demand. Caring is the attitude that teachers and learners build and maintain a relationship of mutual trust through the process of learning.

As to SLE, scholars define it as a learning place or activity space of facilitating effective learning by perceiving learning scenarios, identifying the feature of learners, tracing learning process, and evaluating learning outcomes of learners [6]. In SLE, the boundary between physical and virtual worlds is eliminated, and it can provide students with seamless learning support and services. The featuring component of a SLE is smart tools with which learning scenarios can be identified, learning process can be traced, and the indicators of environment and learning features can be perceived.

With the changing of technologies, learning context as well as the learners' interests changes, but learning does change when it is understood as a naturally occurring process involving changes in what a person knows and can do [7]. The key element and the mechanism of smart learning are the issues that need further exploring; thus, this paper wants to build a theoretical model to explain this issue. In the following section, the paper first discusses the effective learning theory to lay a foundation for the model to build, on the basis of which a theoretical model for smart learning is built. The components of the model are further explained.

9.2.2 Theoretical Foundation

Although smart learning is different than traditional learning in learning context, learning methods, and learning strategies, learning does change when it is understood as a naturally occurring process involving changes in what a person knows and can do [7]. Thus, the construction of smart learning theoretical model should align with the effective learning theory in general.

On the whole, there are two different views on "what is an effective learning," which are "knowledge-conveying pattern" and "knowledge construction pattern." The traditional knowledge-conveying pattern believes that knowledge is objective existence; thus, learning is nothing but students receiving knowledge from experienced teachers and taking exams to demonstrate to what level they master the knowledge. Accordingly, the effectiveness of learning depends much on the teaching capability of teachers and the learning capability of individual learners. For the knowledge construction pattern, it insists that knowledge is not objective existence, and instead, it is acquired by learners through self-experience and construction in a certain context; thus, learning is a process of exploring and discovering on learners' own initiatives, and it should be controlled by learners themselves [8]. However, the "learning should be controlled by learners" does not necessarily mean that it is absolutely self-study without teachers. On the contrary, it is a process that learners acquire learning motivation, cultivate capability of self-directed learning, and develop the twenty-first-century skills of students through interaction.

From the view of constructivism and connectivism, smart learning is not simply to enhance the master of the existed teaching content prepared and delivered by teachers, but to provide several learning paths for learners or even allow students to design learning paths by themselves through the guidance of teachers, encouragement of peers, and the perception and support of SLE. In SLE, the process of teaching and learning is the process of interaction; therefore, the theoretical model for smart learning should made interaction as the core based on certain learning context. It is worth mentioning that the interaction transcends the one-way teaching content transfer, but extends it to the interpersonal interaction and human–environment interaction [9]. And interaction as the core to developing learners' twenty-first-century skills is the basic idea of smart learning, which provides a theoretical foundation for the construction of theoretical model for smart learning.

9.3 Proposed Theoretical Model for Smart Learning

A theoretical model for smart learning is proposed and shown in Fig. 9.1, which takes effective interactions as core of smart learning cycle and is supported by SLE. The smart learning cycle consisted of three factors, which are mental system, learning behaviors, and learning outcomes. Four types of interactions between learners and SLE connect the three factors, which are planning smart learning, executing, monitoring, and evaluating smart learning behaviors, feedback from learning outcomes to learning behaviors, and feedback from learning outcomes to mental system. In the following of this section, SLE in the theoretical model and each factors and interactions of the smart learning cycle are further explained.

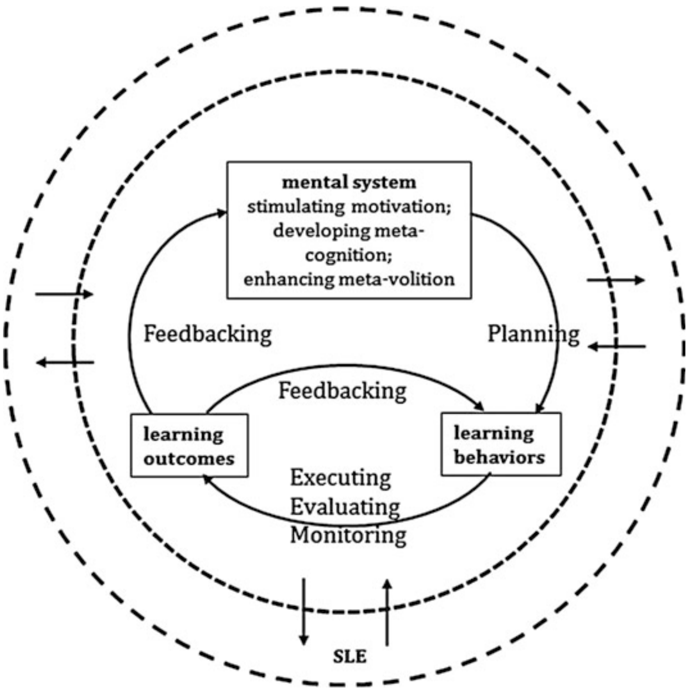

Fig. 9.1 Theoretical model for smart learning

9.3.1 Smart Learning Environment (SLE) in Theoretical Model

Social constructionists believe that learning takes place in the process of conversation and social interaction [10]. By communicating with others, learners can examine and adjust their own views and, therefore, form the understandings toward things and their significance. In this sense, intelligent interactive environment plays a pivotal role in the formation of smart learning. Different scholars have presented conceptions of SLE from various perspectives. SLE is an open-ended, intelligent, and integrated learning space based theoretically on constructivist learning theory, blended learning theory, and modern education methods, which is composed of the corresponding devices, tools, techniques, media, teaching resources, teacher communities, and learner communities [11]. It is a type of learning space not only supports the self-construction of learners but also provides guidance in a timely fashion [11]. Malaysian scholars hold that SLE is based on the application of ICT centered on learners which provides support for lifelong learning in a way that adapts to different learning styles and abilities [12].

Reflected on the aforementioned demarcations, Huang et al. [6] define smart learning environment as “an activity space that is able to perceive learning situation and learner profile, to provide appropriate learning resources and convenient interactive devices, to automatically record learning process and evaluate learning results in an effort to facilitate effective learning" [6]. The elements of smart learning include learning resources, intelligent devices, learning and teaching community, and learning and teaching styles [6].

On the technical level, SLE features four aspects, including the functions of tracking learning process, recognizing learning scenario, connecting learning communities, and perceiving physical environment, with a purpose of promoting easy, engaged, and effective learning. On the interactive level, SLE is characterized by equal interactive subjects, universality of the interactive contents, and edutainment of the interactive environment.

9.3.2 Smart Learning Cycle

Educational psychology research shows that the effectiveness of learning does not only depend solely on external environment. What is more, it asks learning environment and learning process to match with the mental features of learners [13]. Smart learning is the learning activity that involves the changes in mental system of learners. The factors and interaction of the proposed theoretical model are described in the following subsections.

Factors. The effective smart learning cycle consisted of three factors: metal system, learning behaviors, and learning outcomes.

Mental System. The key components of mental system are motivation for learning, meta-cognition, and meta-volition [13]. The mental preparation of effective smart learning includes arousing mental system of learners, developing meta-cognition, and enhancing meta-volition. To effectively arouse mental system of learners, we should arouse their motivation for learning, develop their meta-cognition, and enhance meta-volition. The condition for effective smart learning is that learners have the motivation for accepting learning tasks and want to participate in learning activities. Only when learners believe that the learning activities have positive value on their individual development will effective learning happen [14]. The supportive smart environment helps stimulate and sustain the learning motivation. Teachers, parents, and peers in SLE have multiple ways to communicate with the learners, through which it will help learners establish appropriate understanding on the relations between learning outcomes and learning behaviors. The smart tools cannot only provide instant feedback on the learning behaviors and help learners identify the value of their study, but also can indicate the gap between knowledge, skills, and anticipated learning outcomes by proposing challenging tasks that are relevant to learning goals, so that the learning motivation is motivated.

For the preparation of developing meta-cognition, learners should have three levels of effective cognition: cognition on learning, social cognition, and psychological cognition. Cognition on learning refers to the cognition that learners understand their existing knowledge level, cognition styles, cognition strategies, and learning tasks, and how to attribute their learning outcomes; social cognition refers to the cognition by which learners understand and identify the social context of the SLE; psychological cognition refers to the cognition by which learners understand and identify the emotion that affects the implementation of learning tasks, including their concerns on learning goals, anticipation on learning, and values orientation. Obviously, learners' understanding on their knowledge level affects their learning motivation, and social cognition affects their engagement and benefits in SLE. Psychological cognition affects the involvement and their selection in learning behaviors.

Teachers and smart interactive tools are two factors that decide whether learners' meta-cognition will be fully developed. Teachers as one of the key components in SLE help learners to develop adequate expectation of learning outcomes through systematic instruction or organizing group discussion and reflection. Smart tools in SLE can for one hand track and record learning process and learning outcomes. It can also provide adaptive test for learners and analyze the test outcomes so that the learners and teachers will be informed with the learners' knowledge level.

For the preparation of enhancing meta-volition, meta-volition is the will by which learners engage in learning activities, fully make use of curriculum resources, and persevere in learning. Stable and strong meta-volition is the psychological guarantee depends on which sustaining effective learning happens. Teachers should create a cooperative atmosphere in SLE, an environment that is safety for exploring and experiencing. Besides, the user-friendly interactive interface and interactive tools will reduce the barriers when they are learning in SLE, which will improve learners' activity engagement, and the frequency and efficiency of group communication.

Learning Behaviors. Behaviors are a series of purposeful, motivated activities. Learning behaviors are two-way interactions between learners and learning environment, aiming to cause the relatively stable changes in what learners know and what they can do. Learners in SLE can decide learning goals and learning progress and select adequate learning strategies by themselves. What is more, learners can use the interactive tools provided by SLE to communicate with each other on a certain subject, and learning through online or face-to-face collaboration. These learning behaviors in SLE can be summarized as behaviors of information retrieval, information processing, information release, and interpersonal communication.

Learning Outcomes. Gagne classifies human's learning outcomes into five categories that include intelligent skills (procedural knowledge), verbal information (declarative knowledge), cognitive strategies (executive control processes), motor skills, and attitudes [15]. Each of these categories may encompass a broad variety of human activities. In this theoretical model, various learning outcomes are resulted from the different interactions in SLE.

Interactions. The three factors are connected by four types of interactions: planning smart learning, executing, monitoring, and evaluating on learning behaviors to learning outcomes, feedbacking to mental system, and feedbacking to learning behaviors.

Planning Learners' Smart Learning. Research shows that the level of learning strategy is relatively low, and learners lack the skills in self-directed learning and do not clearly know the relations between the learning environment and learning tasks are the common reason that will result in the failure of learning [16]. Firstly, teachers and smart tools in SLE should guide learners to plan practical and realizable goals and develop supportive social interactive environment on the basis of the recording and analyzing of learning behaviors. Secondly, teachers and learners use smart tools to analyze the learners' learning styles and knowledge status, and identify the correlation between the learning tasks and the former learning. Finally, teachers should help learners to divide the learning tasks into smaller and easier learning tasks.

Executing, Monitoring, and Evaluating Smart Learning Behaviors. The effectiveness of learning behaviors directly determines the effectiveness of learning results. Learning behaviors is a process where learners conduct learning activities according to plan by making the best of learning resources and smart learning tools in the learning environment.

To execute learning tasks effectively is a core link determining the results of smart learning. Within it, learners achieve learning targets through assimilation, obedience, integration, deduction, and retrospect; teachers in this stage facilitate learners in conducting learning tasks through an array of teaching methods and strategies. In practice, the choices of the methods and strategies are subject to teaching contents and goals, and SLE provides supports for conducting learning tasks and promoting successful learning practices. Effective monitoring of learning behaviors is a course where learners, guided by goals of learning, select the optimal routes of learning. In smart learning, learning control is divided into self-control and external control. It is also called internal control. Self-control refers to a process where learning resources and learning activities are selected and learning opportunities are created by learners to satisfy their learning demand, while external control functions in a way that teachers or smart learning tools dictate the topic, contents, targets, and routes of learning through highly structured curriculum that guarantees the whole learning process is on schedule [17]. None of effective learning is realized independently through internal or external control; instead, it is realized through the cooperation of internal and external controls.

Effective evaluation helps learners correctly assess their command of knowledge and skills, and therefore stimulates them to engage in new learning tasks. Speaking about evaluation or evaluation on learners, it should be emphasized that the role of evaluation is not for rating or a device-driving learners to finish their assignments, but for providing further learning feedback [18]. SLE not only assists learners in evaluating commands of the knowledge that is being learned, but also provides them with an emotional safety environment via the sharing of learning results and failures and sufferings in learning. Smart interactive tools record and store learners' achievements in a way that is convenient for learning reflection and further evaluate themselves through a comparison with peers.

Feedbacking from Learning Outcomes to Learning Behaviors. The most direct outcome of effective learning is the realizing of learning targets and the improving learner's learning behavior such as their learning strategies and tactics. In the network interactive environment, teachers and other adults should help learners with an attribution analysis on learning outcomes. By recognizing both achievements and shortcomings, it motivates learners to make further efforts.

Feedbacking from Learning Outcomes to Mental System. Learning outcomes have a feedback effect on learners' mental system and learning behaviors as shown in Fig. 9.1. Feedback on mental system gives rise to change of learners' learning motives, meta-cognition, and the primary consciousness. In this process, other members in the SLE conduct a discussion, analysis, evaluation, doubts, and debate over the learner's learning results so as to help the learner reflect on his or her learning behaviors. Yukawa [19] noted in an empirical study that effective learning will change learners' level of skills and learning strategies so that learners' learning behaviors will become more skill and purpose oriented. In the next round of learning, learners will make clearer learning targets, and their learning behaviors become more effective. Lifelong learning ability is acquired exactly when learners effectively and voluntarily control their own learning behaviors.

9.4 Discussions and Conclusion

The learning and teaching activities of SLE are the interactive activities and learning behaviors which happen in a smart learning cycle of learning environment. Therefore, in the proposed theoretical model, an effective smart learning cycle should consider three factors of learner: metal system, learning behaviors, and outcomes. These three factors are connected by four types of interactions: the plan of smart learning from learner's mental system, the execution, monitoring, and evaluation of learning behaviors, the feedback from learning outcomes to learning behaviors, and the feedback from learning outcomes to mental system.

In addition, each factor is also supported by SLE in various ways such as supervision, evaluation, and correction. For example, teachers or other adults supervise the learning progress using smart tools in order to provide decision information relating to the correction of goals and strategies of learning. In another example, teachers can organize group supervision inside the learning community, which results in an empathic emotion of the success and failures of learning through among group members through discussion and interaction; network and intelligent technologies help to reduce learners' cognitive burden on learning supervision by effectively recording the learning results of the group and other peers, as well as their learning strategies. At the meantime, learners handle problems occurring in the learning process by editing, adjusting, and reconstructing materials relating to learning behaviors and strategies in an effort to realize their learning goals.

In conclusion, this study provides a theoretical foundation for designing the theoretical model of smart learning. Moreover, this model could also provide a framework for the further studies which aim at building an effective SLE by considering different features and factors of smart learning.

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Chapter 10
AlecsoApps: Toward Empowering Mobile Applications Development in the Arab World

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Abstract Recent years have witnessed an increasing interest in the mobile computing realm. Gartner says that mobile device (smartphones and tablets) sales are on a continuous rise from year to year, and the future of enterprise applications, both for enterprise workers and consumers, is mobility. Actually, multiple platforms are making mobile devices' markets at a global scale for all consumers all over the word. Nevertheless, the number of Arabic mobile applications available in such markets remains few so far, especially those related to the education and smart learning fields. Thus, recognizing the potentials of mobile applications development and its impact, ALECSO organization has been working on a very promising project titled "AlecsoApps" to empower mobile applications development in the Arab world. The project aims to provide developers with a necessary technological and institutional environment for the promotion of an emerging digital creative Arab mobile industry, related to the fields of education, culture, science, and learning games. In this paper, we present an overview of the AlecsoApps project, and we describe in details each of its component and related activities.

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Keywords Mobile devices · Mobile applications · Mobile markets · Cross-platform development · Native apps · Web applications · Generated applications

10.1 Introduction

In spite of increasing Arab young technology geeks, addicted to computers and mobile devices, Arabic-based mobile apps available so far are still few. Being concerned by this issue, The Arab League Educational, Cultural and Scientific Organization (ALECSO) [1] has proposed a promising project (AlecsoApps) aiming to promote the Arab mobile apps use and development, especially, in relation to the areas of education, culture, and science. Actually, this project is fitting very well the mainspring of the organization and its current framework since ALECSO is indeed leading the implementation of a "Plan for the Development of Education in the Arab Countries." The overall goal of this plan is to develop the Arab educational system, mainly through the effective use of ICTs in education [2]. To this end, ALECSO has proposed a set of unprecedented and innovative Pan-Arab projects aiming to increase access to learning [3] and enhance the quality of education. These projects are covering the following areas: mobile learning, open educational resources (OERs) [4], massive open online courses (MOOCs) [5], and cloud computing [6]. This paper is arranged in the following way: First, we describe briefly the overall ongoing ALECSO projects. In Sect. 10.2, we provide some alarming statistics regarding the use of smartphones in the Arab countries. In Sect. 10.3, we present some related works to the proposed mobile apps project. In Sect. 10.4, we evoke the main existing initiatives and works related to mobile apps environments allowing non-expert users to learn smartly and to produce readily their apps. In Sect. 10.5, we focus on the AlecsoApps project and its components. In Sect. 10.6, we describe in details the AlecsoApps Editor environment and all related technical aspects; we present likewise the implementation issues, conducted experiments, and some users' feedback especially from the educational point of view. Finally, conclusions and future work are presented.

10.2 Motivations

According to a study conducted by ALECSO [2], more than two hundred millions of Arab people are using smartphones and this number is still growing dramatically and expected to reach 340 million by 2020. In contrast, the number of Arabic mobile apps available in the world markets [7] is unfortunately very limited (less than 1 %) and did not elicit the real use and interest in such technology within Arab countries. Consequently, this lack of mobile digital Arab content and more specifically mobile digital educational content represents a critical barrier that prevents

Arab folks from benefiting of considerable unprecedented professional and social opportunities, and thus to move forward toward sustainable development.

10.3 Related Works

At time of writing, many existing initiatives were founded with the aim of promoting mobile applications development via training, education, and competitions. As examples, we would cite the Youth Mobile[1] project, one of the UNESCO's projects for sustainable development via education and technologies. This project aims to aiming to teach young girls and boys worldwide how to develop mobile apps. Imagine Cup[2] is another project led by Microsoft Company, it is an international student technology competition offering to students all over the world the chance to get involved in mobile technology field and to win awards. Many Arab students are participating regularly in this competition and won several times lots of prices. Unfortunately, these aforementioned projects are not promising Arabic educational contents nor targeting Arab people. Actually, some other local initiatives have been trying to address these latter issues but did not yet gain a Pan-Arab dimension and are not so comprehensive. For example, we can cite the Arab Mobile Application Challenge (AMAC)[3] initiative which aims to promote mobile application development in Arab countries, but did not yet cover capacity building activities.

10.4 Cross-Platform Mobile Applications Development

The cross-platform mobile app development's concept has tremendously simplified the process of apps development and versioning since developers can run seamlessly their apps across multiple mobile platforms. So it looks like "one code fits all" since it is possible to code likely an application that can be run on multiple platforms without tweaking the code belonging to each obtained native version.

Many tools are available to develop flexible mobile applications with seamless compatibility such as:

- PhoneGap (Apache Cordova): an open source tool that enables developers to create mobile applications compatible with Android, iPhone, iPad, Palm, BlackBerry, and Symbian [8, 9].

[1] http://en.unesco.org/youthmobile.

[2] https://www.imaginecup.com.

[3] http://www.arabmobilechallenge.com/.

- Sencha Touch: HTML5-based cross-platform framework that provides fully functional APIs and offers a component-based approach for building mobile applications.
- MonoSync: This framework supports C and C++, PHP, Java, JavaScript, Python, and ROR for mobile development apps.

10.5 AlecsoApps Project Description

In spite of an increasing techie Arab young population, highly interested and even addicted to mobile devices and smartphones, the number of Arabic language mobile applications developed so far is still few. This fact could be explained (according to a study realized in ALECSO) based on the following:

- Lack of relevant regional initiatives to promote mobile technology and to develop entrepreneurship and innovation skills, especially for Arab young developers;
- The well-known app stores are toughly accessible or reachable;
- Few commercially successful Arab mobile markets; and
- The inadequacy of curricula in schools;

Endeavoring to address some of these drawbacks, ALECSO organization has proposed a comprehensive, huge, and strategic project (AlecsoApps) [10] aiming to provide a necessary technological and institutional environment for the promotion of an emerging digital creative Arab mobile industry, related to the fields of education, culture, and science. Furthermore, in order to build and reinforce capacities in the realm of mobile technologies, ALECSO is organizing several training workshops in Arab countries. These workshops are available in two levels: beginner and advanced. They are ensured following a blended model.

10.5.1 AlecsoApps Store

The AlecsoApps Store is a Web-based application intended for hosting and gathering Arab mobile applications. This platform is also installable on supported mobile devices that run Android OS [11]. This Arab marketplace provides the opportunity to Arab developers involved in mobile technology to innovate and to share their creations without any fees, restrictions, or barriers.

To ensure a good quality of applications on the store, we set up a strict publishing process. Before publication, our experts must assess each application.

The architecture of the AlecsoApps store platform is designed to ensure a high quality of services. It is composed of two main modules hosted on two different servers. The first module is Web based, and it ensures the management of the Web interface of the store. The second module is cloud based. It ensures all features that need processing the binary files such as metadata, size, signature, etc. This architecture is intended to be gradually entirely cloud based.

10.5.2 AlecsoApps Editor

The AlecsoApps Editor is a Web platform that provides an environment of rapid application development (RAD) [12]. It represents a comprehensive mobile applications development studio. It enables users to create their applications in few intuitive steps. The technical details about the editor's software architecture will be presented in Sect. 10.6.

10.5.3 AlecsoApps Award

It is an annual Pan-Arab competition aiming to motivate and encourage Arab developers to meet high-level standards in term of mobile applications quality, innovation, and entrepreneurship. The competition is set over two stages: The first stage is national, lead and held locally in Arab countries to select the best mobile applications in each Arab country, in the areas of education, culture, science, and educational games. The second stage is rather at a Pan-Arabic level: Winning applications are selected among those getting successfully the first round. The amount of the AlecsoApps Awards would be about 50,000 $US.

The submission and the evaluation of applications are done online. Many reviewers from different Arab countries participate in the evaluation of each application. The evaluation is based on many criteria such as innovation, creativity, features, content, user interfaces, technology, and even application packaging. During this phase, Internet users can choose and so nominate the winner of the audience award applied through the voting system.

10.6 AlecsoApps Editor: Arab-Based Cross-Platform Apps Development

As explained above, applications generated by the AlecsoApps editor are able to run on any device since they are built using Web technologies and wrapped and compiled with Apache Cordova. Thus, these applications can access to all native device capabilities and features. Thereby, advanced users can then use the source code of the app and add more plug-ins in order to enrich the application with native functionalities.

10.6.1 Architecture Overview

The editor connects the user interface with the back-end systems. The system adopts a very flexible approach to provide "developers" with high level of customization. Indeed, graphical designers, developers, and content managers can benefit from the Web-based visual platform to collaborate and share the application view in order to tune the application simultaneously. The platform of the editor is based on four layers: editor front, libraries, back-end system, and the integration framework.

The front is the user interface service which allows developers to select the provided components and build pages of the application. We should notice that other third-party tools like online picture processing are provided as well. A set of predefined templates and plug-ins are provided; however, the developer can customize and/or add new developed templates.

In the next layer, we find libraries that represent mainly the basic Web technologies that will be used to render the Web version of the mobile app. The apache Cordova, which is a Javascript library, allows the creation of plug-ins ensuring access to native features such as storage, network, and camera. The following layer is the back-end system, which is the engine of the editor. In fact, this part of the platform represents the components used to manage users' accounts, authentication as well as apps compiling. As for the last layer, it represents the integration functionalities gathering the most known APIs which allow developers to embed external data resources natively. Indeed, adding a map from google, a video from YouTube, or a feed from any Web site is very easy thanks to the integration framework.

10.6.2 Infrastructure

Actually, the editor has been deployed on a cloud-based infrastructure. Two main instances are dedicated to both the editor's front and the editor's compiler. To guarantee a high level of availability, the editor's platform is built behind a very scalable cloud DNS lookup service. This service, called "Cloud Front," automatically roots the traffic to zone2 (Ireland) where the whole platform is cloned. The compiler is an intensive service in term of computation requirements. It allows the editor's front to convert the generated apps form HTML5 into WP8 and Android binaries, which are composed of native containers that embed Web views. The average time necessary to compile an application is around 45 s on a single instance. The compilation average time can cause bottlenecks especially during rush hours and simultaneous access (e.g., training sessions). Subsequently, a mechanism of auto scaling and load balancing is necessary in order to handle excessive simultaneous calls to the compilation process.

10.7 Conclusion

In this paper, we presented projects led by the ALECSO ICT Department. We put the focus on the AlecsApps Project which aims to promote Arabic mobile applications in the areas of education, culture, science, and educational games. The project framework is based on three main components: the store, the editor, and the award. More than 1100 participants from 19 Arabic countries have registered in the award. The editor's platform was used in many training sessions in several Arabic countries that targeted teachers, PhD students, as well as experts involved in the use of ICT in the educational process. The editor is available online and is still being used regularly in the Arab world, and around 16 Arabic apps are being compiled daily. The store is being continuously updated with new Arabic apps.

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Chapter 11
Designing Creativity Developing Activities and Studying the Effects on Students in Web-Based Learning Environments

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Abstract This study aims at analyzing, the effects of Web-based teaching method on students' creativity, supported by smart learning environment compatible activities which were designed to improve students' creative thinking abilities. In this research, pre-test–post-test control group design was used. This study was carried out with 62 students at 6th grade at an elementary school in Istanbul. As a part of the research, two classes were chosen by randomization method. Traditional teaching methods and techniques were used in one of the classes, while in the other class Web-based teaching method was applied. In both groups, activities to improve students' creative thinking skills developed by the researchers were used. While these activities were being designed, 40 experts who conducted studies in creativity field were consulted. Research data were obtained by means of Torrance Test of Creative Thinking Verbal A and B forms.

Keywords Web-based learning · Creativity · Torrance test of creative thinking (TTCT) · Moodle · SCORM · Software tools

11.1 Introduction

In order for the education system to give students the opportunity to develop their potentials and play effective roles in country's development, the content and methods of education must be designed in a way to give students skills for critical thinking, scientific thinking, relational thinking, reasoning, and creative thinking. Creativity can be expressed as an attribute that gives individual the power to break

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from the ordinary chains of thought and to think productively by means of creative thought chains in a way that while ideas remain flexible, original, and sensitive, the result pleases both the individual and the others [1]. When we look at studies on creativity, although creative thinking is regarded as an innate ability, it is also emphasized that it can be learnt, and the creative thinking skills of the individual can be improved by means of suitable environments and programs [2–4]. According to this, it is thought that technology, one of the essentials of our age, must take part in designing the environments that will improve creativity. As creativity is a process in which the individual becomes aware of the problems for which he does not have solutions and the gaps and conflicts between information, and so he looks for solutions to his present condition out of his existing knowledge, develops hypotheses or alternative solutions, and tries these hypotheses in order to come to a result [5], it is obvious that Web technologies must be used for the individual to attain these capabilities and sustain them for a life time.

Smart learning environments is a term whose meaning is not clear yet among the educational technology experts. In addition today's innovations in mobile devices and smart technological platforms which are using at teaching technologies are among the smart learning environments. Dodds and Fletcher [6] defined a Web-based learning environment in smart learning environments.

In this research, it is aimed to design activities in Web-based learning environment, a type of distance education, in order to develop creative thinking skills of 6th-grade elementary school students in math class and to analyze the effects of this teaching method on students' creative thinking skills, in terms of fluency, flexibility, and originality. It is also mentioned how the activities in line with these objectives were designed. In accordance with the problem statement, the hypotheses of this research were determined as follows: (1) There is no meaningful statistical difference between total creativity pretest scores of control and experimental groups that participate in this research-mentioned dimensions. (2) There is a meaningful statistical difference between creativity pretest–post-test total scores of control and experimental groups that participate in the research, in terms of post-tests. (3) There is a meaningful statistical difference between total creativity post-test scores of control and experimental groups that participate in this research in terms of fluency, flexibility, and originality dimensions.

11.2 Method

As this study deals with the effectiveness of teaching materials designed to develop student's creative thinking skills and effects of Web-based education on students' creative thinking levels, it has been deemed appropriate to use a type of experiment model, and in this case, pre-test–post-test control group experiment design was chosen. Experiment design of the research is presented in Table 11.1.

Table 11.1 Experimental design of the research

Groups	Pre-measurements	Experimental procedure	Post-measurements
Control	Torrance Test of Creative Thinking Verbal A form	Traditional teaching methods and techniques; activities improving critical thinking skills	Torrance Test of Creative Thinking Verbal B form
Experimental	Torrance Test of Creative Thinking Verbal A form	Web-based learning; activities improving critical thinking skills	Torrance Test of Creative Thinking Verbal B form

11.2.1 Study Group

The study group of this research is made up of 62 students studying at 6th grade in two different classes at Orhangazi Elementary School in Maltepe district of Istanbul. The students had been divided equally into a control and experimental groups. In one of the classes chosen by randomization method, traditional teaching methods and techniques were used in mathematics lessons, while in the other class, Web-based teaching method was applied.

11.2.2 Data Collection Tools

In this research, Torrance Test of Creative Thinking (TTCT) Verbal A and B forms were used in order to collect data. Creativity is a concept that can be measured. In the relevant field, TTCT that is used most commonly to measure creative thinking skills of individuals [7], and most frequently referred to [8, 9], has principal importance, as they can measure creativity directly [10]. In line with this, in this study TTCT Verbal A and B are forms were used in order to assess the improvement in creative thinking skills of students who make up the study group. TTCT consists of two different tests as "Verbal" and "Figural." TTCT is made up of two alternative forms as A and B. These forms can be applied to a wide age group ranging from nursery school to adults. Each one of the forms is made up of six activities in total. During the application of the test, the participants were given, for activities 1, 2, 3, and 6 (for each activity), 5 min, and for activities 4 and 5 (for each activity), 10 min. The total implementation duration of the test is 40 min. In general, the total score of TTCT Verbal form was calculated by measuring the scores for fluency, flexibility, and originality in 6 activities.

TTCT Tests Validity Reliability Studies. The fact that TTCT is a valid and reliable measurement tool was proven by Torrance by various studies [11] and the same finding has been validated by other researchers [10, 12]. Validity and reliability studies of TTCT which was translated by Aksu Yontar for the first time, and later by Sungur were executed as well [13]. Aslan [10] carried out linguistic equivalence, reliability, and validity studies in order to make up the Turkish version of A–B forms. As a result, the test was found to be reliable for all age groups and all types of points.

11.2.3 Experimental Application and Designed Smart Learning Objects

The experimental application of the study took a total of 8 weeks. During the application, students in ***control group*** studied math in class environment with a math teacher in accordance with face-to-face teaching model. However, they were supported with paper-based activities that were developed by the researchers to improve their creative thinking skills. While activities were being prepared for this group, special attention was paid to assure that activities were identical to activities of the experimental group. Only computer-based activities were transferred onto the paper, with the same colors as on computer. In ***experimental group***, students studied on modular object oriented dynamic learning environment (Moodle), an offline class management system with open source code, content which was prepared by researchers, according to opinions of 5 math teachers and 5 academicians and students got in contact with their teachers on Web environment. They send their questions via the messaging system on Moodle platform. This platform allowed students to access the class content 7/24 on Web environment.

According to Piaget, exchanging ideas among themselves, discussing, and evaluating each other's ideas increase student's cognitive development speed and quality [14]. Thanks to Moodle platform the students were given the chance to get in touch with each other constantly and to have the knowledge of which friend did which activities lately. Besides sending private messages to their friends whenever they wanted, the students were able to perform brainstorming in discussion environments prepared by researchers and conduct peer interaction and peer education. While appropriate activities were being designed to develop creative thinking skills of students participating in research, people who conducted researches in creativity and specialists in this field were consulted. In line with this, interviews were held with 40 experts among whom, there were teachers, artists, and academicians who studied subjects such as creativity, creative drama. In accordance with the data obtained from the interviews, animated multimedia contents and visuals based on basic principles of multiple intelligence theory that can appeal to students' different sensory organs were developed using software tools such as Adobe Flash Professional, Captivate, Illustrator Camtasia, Crazy Talk, and Animator. These contents were converted into Sharable Content Object Reference Model (SCORM) so that they could be used in smart learning environments and were embedded into Moodle, a dynamic learning environment. Apart from these, environments such as forums and competitions were prepared to enhance peer interaction and encourage students to socialize on Web. Also the lessons were supported by educational

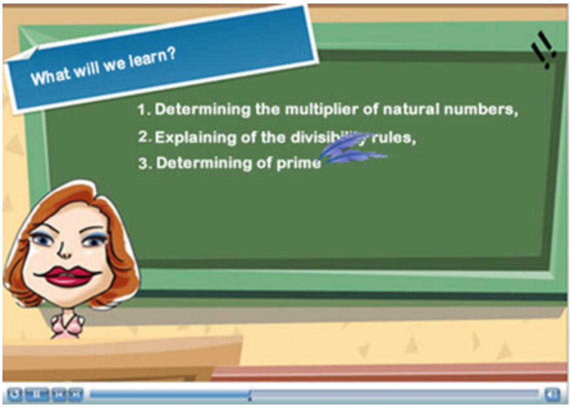

Fig. 11.1 Virtual teacher avatar who informs students about attainments

games, prepared by researchers, addressing the current subject of study, with the aim of giving students motivation for success, making them like Math unconsciously and making them learn naturally.

In consideration of the information obtained from the experts that individuals have desire to learn only what information they need and what they are curious about, in the beginning of each lesson, what the students would learn in that class was told to the students by means of various avatars (Fig. 11.1). By means of this, increasing the students' interest in the class and effecting their learning positively were aimed at [15].

In Math, it is necessary for concepts to be generated in the mind so that these concepts can be educationally attained. This requires discovery learning [15]. 50 % of the interviewed experts emphasized that individuals' creativity can be improved by activities based on discovery learning, and 38 % of the experts emphasized that creativity can be improved by using daily life examples in learning environments.

The students can discover and develop their skills only through opportunities that allow problem solving. In this study as well, offering mathematical attainments to students on a Web-based environment, by means of these methods, was thought to be appropriate in developing students' creative thinking abilities. With this aim, Web-based educational scenarios were prepared in line with discovery learning and problem-based learning methods. Instead of giving the students the rules directly, various situations were created from daily life so that the students become aware of the problem in the first place. For example, the first attainment of "integers" is "The student recognizes the integers." While this attainment is given to the students, first "four operations machine" was designed in computer as a smart learning environment (Fig. 11.2).

They could choose randomly the balls and operations then could guess the results with this experiment. Another type of activity brought into the foreground by experts during interviews is the games. So, games were given plenty of space in the activities.

Fig. 11.2 Screen display of "four operations machine" used for implementation activities

11.2.4 Data Analysis and Resolution

The analysis and assessment of TTCT Verbal A and B forms were carried out by researchers as they had received certificates and creativity training from the relevant people and institutions. However, in order to ensure scoring reliability, the forms were assessed according to the scoring manual by another specialist studying in creativity field. The interrater reliability was determined by intra-class correlation coefficient. According to this, interrater reliability coefficient of TTCT Verbal A form was found as 0.93, and that of Verbal B form was found as 0.94. SPSS 21.0 package program was used in analyzing students' creativity scores. As a pre-condition in determining test statistics to be used in data analysis, the fact whether the data meet the normal distribution assumptions or not were surveyed. The compatibility of the data obtained as part of the study to normal distribution was determined with the help of Shapiro Wilk W test statistics, and it was observed that all the data in the study display normal distribution. In line with this, in analysis of the data, paired samples t-test and independent samples t-test from parametric tests were used.

11.3 Findings

The number of samples in each subproblem of this study is large enough for using parametric methods ($n > 30$). Whether the data have normal distribution or not were checked by using one of the most powerful tests [16] (Shapiro–Wilk test), it was decided which one of the parametric or non-parametric statistical methods was going to be used. According to this test (Table 11.2), it can be said that in case, $p > 0.05$ as a result of the test, the data meet normality assumption and in case where $p < 0.05$, the data do not meet normality assumption. Within the scope of the study, in order to determine the statistical technique that will be used for analyzing of the data, the normality test results according to the control and experimental

Table 11.2 The results of normality tests applied through TTCT Verbal A and B forms total scores of control and experimental groups

Score types of groups	Groups	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Verbal A form total score	Control	0.140	31	0.129	0.940	31	0.080
	Experimental	0.104	31	0.200	0.982	31	0.869
Verbal B form total score	Control	0.164	31	0.033	0.959	31	0.266
	Experimental	0.072	31	0.200	0.985	31	0.924

groups' TTCT Verbal A and B forms total scores in terms of fluency, flexibility, and originality dimensions are given in Table 11.2.

When the table is studied, it is observed that both control and experimental group students' total scores of TTCT Verbal A and B forms show correlatively normal distribution according to fluency, flexibility, and originality dimensions ($p > 0.05$). In line with the first hypothesis of the research, results of independent samples t-test addressed to the meaningfulness of the difference between the total scores of control and experimental groups according to TTCT pretest results are displayed in Table 11.3.

When Table 11.3 is studied, it is observed that statistically there is no meaningful difference between total score averages of control and experimental groups' TTCT pretest ($t_{(60)} = 0.02$; $p > 0.05$). When pretest averages of the groups are studied, it is observed that the average of total points of control group ($\bar{X} = 64.77$) is higher than that of the experimental group ($\bar{X} = 64.58$). When findings that are obtained within the scope of the first hypothesis of the study are evaluated in general, it can be said that statistically there is no meaningful difference between creative thinking levels of control and experimental groups before the experimentation process. Paired samples t-test results, used for comparison of total creativity scores of ***control and experimental group*** students in line with the 2nd hypothesis of this research, are given in Table 11.4. When Table 11.4 is studied, a meaningful difference is observed between pretest and post-test total score averages of control group creativity test ($t_{(30)} = -12.36$; $p < 0.05$). When the average of the total points is studied, the average of post-test total points of control group ($\bar{X} = 170.96$) is observed to be higher than pretest total score average ($\bar{X} = 64.77$). In line with the 2nd hypothesis of the research, the change in creativity pretest and post-test results of ***experimental group*** is studied. Paired samples t-test results, used for

Table 11.3 T-test results displaying the total scores of control and experimental group students' TTCT Verbal A form

Type of the test	Group	n	$\bar{X}$	S	sd	t	p
Verbal A form total score	Control	31	64.77	32.04	60	0.02	0.978
	Experimental	31	64.58	23.20			

Table 11.4 T-test results displaying the total creativity scores of groups TTCT Verbal A and B forms

Group	Type of the test	n	$\bar{X}$	S	sd	t	p
Control	Verbal A form total score	31	64.77	32.04	30	−12.36	0.000*
	Verbal B form total score	31	170.96	66.31			
Experimental	Verbal A form total score	31	64.58	23.20	30	−16.46	0.000*
	Verbal B form total score	31	239.48	69.20			

*$p < 0.05$

comparison of total creativity scores of experimental group students, are also shown in Table 11.4.

It is seen that the averages of TTCT pretest and post-test total scores of experimental group display a meaningful difference in terms of fluency, flexibility, and originality dimensions $\left(t_{(30)} = -16.46; p < 0.05\right)$. When score averages of students are examined, it is seen that the total score averages that students obtained are higher in favor of post-tests. When findings of the 2nd hypothesis of the research are assessed, it can be said that math classes in a traditional classroom environment and math classes in a Web-based learning environment that were enriched with activities aimed at developing students' critical thinking skills meaningfully improved students' creativity thinking abilities.

In line with the 3rd hypothesis of the research, independent samples t-test results are the total score averages of control and experimental groups according to TTCT post-test results are observed that statistically, TTCT post-test total score averages of control and experimental groups display a meaningful difference $(t_{(60)} = -3.98; p < 0.05)$. When looked at averages of post-test total scores of the groups, it is observed that the average of experimental group scores $(\bar{X} = 239.48)$ is meaningfully higher than that of the control group $(\bar{X} = 170.96)$. When findings of the 3rd hypothesis of the research are assessed, it can be said that math classes in a Web-based learning environment that were enriched with activities aimed at developing students' critical thinking skills improved student's creative thinking abilities meaningfully more in comparison with traditional classroom environments that are enriched with the same type of the activities.

11.4 Result, Discussion, and Suggestions

As a result of the findings of the study, it was observed that students' creative thinking skills were improved in Web-based learning environments, meaningfully more when compared to the traditional learning environments where the same activities were offered to the students as paper-based. As in both groups, activities improving critical thinking skills were used, the difference between the groups is thought to stem from Web-based learning method. Also, the results obtained show that the activities developed were designed properly for the purpose. When the relevant field is examined, studies that compare Web-based learning for developing student's creative thinking abilities to traditional teaching methods were not found. On the other hand, some research results were found that encourage the result of this study, that learning environments where technology is used effectively, and that effect students' creative thinking abilities more positively compared to traditional teaching methods. Pardamean et al. [17] suggested that both creative thinking and problem-solving skills of logo programming group developed more positively compared to control group. Similarly, the results obtained in studies by Clements [18] and Liu [19] validate the results of this research. They indicated that Web environments by ensuring the lessons to be more interesting make the students like the lessons, and so help them learn more easily and also enable students to reach to the learning environment from wherever they can connect to the Internet. They also pointed out that especially in today's busy-class environments, it is quite difficult for teachers to attend each student one-to-one, so Web-based learning environments both relieve the teachers and encourage students to turn self-study into a habit. A Web-based learning environment enriched with audio, video, graphics, two-dimensional, or three-dimensional animations creates a more permanent and more enjoyable studying process for students. The following suggestions can be made with in consideration of the results obtained from this study:

1. Within the scope of the research, it was observed that Web-based learning increased the students' creative thinking levels in math classes. Herein, designing Web-based learning environments very well will increase this effect even more. According to this, the activities must be prepared at the same time with common work of, minimum one subject field specialist, software developer, education technologist, and design specialist, and these activities must be made available in smart learning environments as study subjects in a way that students can actively participate into the learning process and where mutual communication is possible.
2. In order to reach more meaningful results for usage of Web-based learning environments, similar studies can be carried out in different fields as a geography, history, or biology and on students at different learning levels.
3. In order for Web-based learning method to be carried out in schools in an efficient way, the present infrastructures of educational institutions and physical conditions must be improved to support this system, and also the number of in-service training for teachers who work in schools must be increased in order to increase their technology literacy.

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Chapter 12
Toward a Learning Ecosystem to Support Flipped Classroom: A Conceptual Framework and Early Results

Michail N. Giannakos, John Krogstie and Trond Aalberg

Abstract The systematic use of technologies in order to orchestrate learning has become widely employed in the past years, and diverse technologies have been applied in a variety of teaching practices, for instance, learning tools which allow you to flip the classroom or monitor other active learning practices. However, the developed systems are only a subset of different kinds of learning materials and learning tools that an educator should take into consideration, and most importantly, they do not offer an overview of the different learning dynamics. The development of a learning ecosystem framework, which will allow us to describe "the complex of living organisms" as well as their interrelationships, will help us to better understand and further develop our teaching approaches. In this paper, we present a learning ecosystem framework and the first captured results of its application. The framework incorporates basic e-learning tools and traditional learning practices, making it accessible to anyone wanting to implement a flipped classroom experience in his/her course. Its application is based on easy-to-use tools, allowing for the incorporation of any additional specificities. This work aims to provide insights for other scholars and practitioners to further validate, examine, and extend the proposed framework. This approach can be used for those interested in incorporating flipped classroom in their teaching, since it is a flexible procedure that may be adapted to meet their needs.

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12.1 Introduction and Background

Traditional lecture style is the most common teaching approach used in higher education classes; however, the traditional lecture style of teaching can often place students in a passive role, which typically involves students retaining isolated facts that can later be forgotten. Over the last few years, instructors have been moving away from the traditional lecture approach by implementing active learning practices, such as project-based learning and flipped classroom, and increasing the technology use as a way to extend and enhance students' understanding.

Although flipped classroom is not a new notion, there has been recently a tremendous discussion around it. During the last years, flipped classroom has been relaunched as an exciting new topic in educational research; however, sometimes we face that there is a lack of consensus on what exactly the flipped classroom is, and there is also a limited amount of scholarly research on its effectiveness [1]. The initial and quite simple definition of the flipped classroom is given by Lage et al. [2]. "Inverting the classroom means that events that have traditionally taken place inside the classroom now take place outside the classroom and vice versa" (p. 32). This definition portraits the rationale of flipped classroom; however, it implies that the flipped classroom merely represents a reordering of at-class and at-home activities. In practice, flipped classroom is an educational technique that consists of two parts: (1) active learning activity inside the classroom, most of the times in groups focusing on critical knowledge and (2) well-defined self-regulated learning outside the classroom assisted by technology and focusing on fundamental knowledge. Although flipped classroom practices have been used in a number of education studies, a framework describing the learning dynamics is typically not described; the development of a learning ecosystem framework will allow us to better understand and further develop our teaching approaches.

A traditional ecosystem is "the complex of living organisms, their physical environment, and all their interrelationships in a particular unit of space" (Encyclopedia Britannica [3]). By applying this simple and good working definition to learning, we can describe a learning ecosystem "*as the complex of living organisms in a learning environment (e.g. students, educators, resources), and all their interrelationships in a particular unit of space (can be digital or physical).*" In a learning ecosystem, it is important to consider the interrelationships of the main actors (students and educators) but also the role of the learning space (both digital and physical), thus also including aspects of the so-called digital ecosystem [4]. The learning space, which by analogy is the physical environment in a traditional ecosystem, includes (organisms) information and digital resources like slides, lecture recordings, blog entries and forum discussions; but also physical materials like books, notes and handicrafts, to mention a few. The space is where teaching or learning is happening and where such processes and interrelationships are conducted. The interrelationships exist [5, 6] between the main actors (students and educators), the main actors with the resources, and the resources themselves (e.g., recommender systems).

The contribution of this work is twofold: First, we present a conceptual framework of a learning ecosystem which can host flipped classroom teaching, and second, we provide some first analytics-based evidence regarding its effectiveness and acceptability. Building upon existing technologies and practices such as video assignments, clickers, and active learning approach, in the next section, we propose a learning ecosystem for flipping the class. In the third section, we present an empirical study following the proposed approach, where by collecting diverse-sourced data, we portray students' experience throughout the course of the semester. The last section of the paper draws conclusions and discusses ideas for further research in the area. This study aims to provide a springboard for other scholars and practitioners to further examine the efficacy of this specific blended learning approach. Our conceptual framework is a flexible procedure that can be utilized and adapted to meet different needs.

12.2 Toward a Learning Ecosystem for Flipped Pedagogy

12.2.1 Theoretical Description

Siemens [7] described learning ecosystem as a mean for orchestrating a variety of learning approaches given by the varied characteristics of learning processes. Learning ecosystem is seen as an environment which is "consistent with (not antagonistic to) how learners learn." His approach focused on the learning process dimension and took into account learners' characteristics and the potential dynamics of the learning environment.

Our approach considers that the main focus of the learning domain should be the relationships and interactions related to the information flow as well as knowledge transfer and transformation. Similarly with a biological ecosystem, in a learning ecosystem, individuals can form groups spontaneously and can interact with each other or with learning utilities at the individual or group level. They can also perform specific behaviors in order to contribute to or perturb to the success of the learning ecosystem [6]. Changes in the learning ecosystem conditions (external influences) shape the "behavior" of the system and its components. To be successful and to be valuable for the system, each individual and group must adapt to the environmental conditions to find their niches. In order to fit them all together, proper learning infrastructures must also be available (Fig. 12.1).

The development of the framework is emphasized in the generic view of the learning ecosystem; hence, it is possible to apply it to any active learning situation, such as project-based learning, or peer instruction, with a focus on flipped classroom. Another important aspect is to assert that the interrelationships and interactions with all the organisms, external influences as well as the infrastructures of the learning ecosystem are in principle dynamic (Fig. 12.1). This generic view helps to get a better picture about a specific learning situation and allows educators and

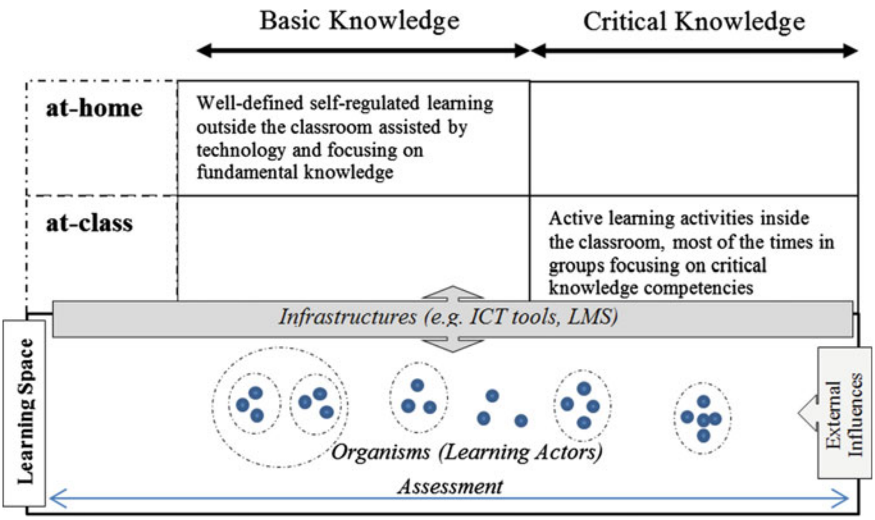

Fig. 12.1 The learning ecosystem to support flipped classroom

practitioners to achieve a more holistic approach for the development of more effective learning. A graphic representation of this definition is shown in Fig. 12.1.

12.2.2 Putting the Proposed Framework into Practice

The proposed framework was applied in a second-year course of a computer science department, named "Web technologies." This course has specific external influences (conditions), such as learning goals, methods, workload, and content. The focus of this course is on the World Wide Web as a platform for interactive applications, content publishing, and social services. By the end of this course, students are expected to be able to design and develop Web pages and Web applications. Students have to deliver specific assignments, work with a self-selected group project, and take written examination; these three components are also the evaluation criteria. The course materials, digital communication and the assignments and project work are orchestrated from a learning management system (LMS).

Following the proposed framework (Fig. 12.1), we defined the at-home activities in order to assure the transfer of the fundamental knowledge. This is the typical flipped classroom process, where students are involved with the learning materials in order to obtain the basic knowledge before the class. This basic knowledge was made available using video lectures; in addition, we employed an integrated assessment to the video lecture (see Fig. 12.2) and weekly exercises. These self-regulated but also well-defined concepts allowed students to better understand the video and reflect about their learning [8]. Upon students' completion of the

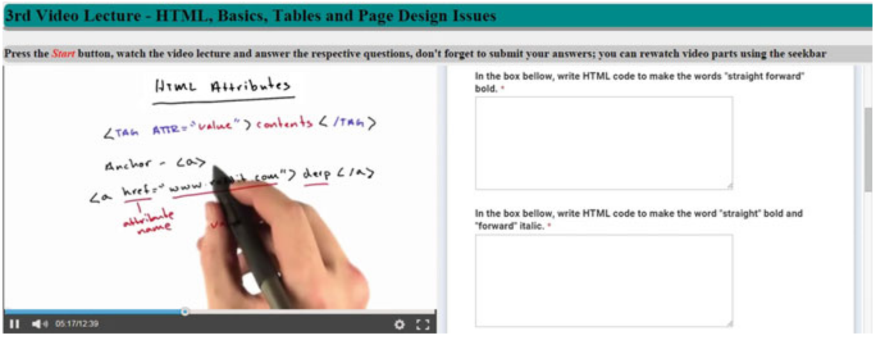

Fig. 12.2 An example of a video assignment

video lecture and the respective assessments, instructors can access all the collected data, visualize students' activity and progress, and ultimately identify students' interaction with the materials. Such information allowed instructor to be well prepared for the at-class session by addressing all the misunderstandings and misconceptions of the students [9, 10].

Based again on the proposed framework, the at-class activities are developed with a main focus on recalling the basic knowledge and then engaging students with active learning and critical thinking processes. The recall part is conducted using a mobile game/quiz at the beginning of the class. The instructor prepared a session with questions related to the basic knowledge, supported with different forms of audiovisual materials (e.g., videos) [11]. The class was equipped with a projector, which was used to project the main screen of the game (see Fig. 12.3a), and each student used his/her own mobile phone to give the answer to the respective question (see Fig. 12.3b). At the end of the course, the instructor could download all the collected analytics of the game and explore students' progress and understanding.

In order to engage students more deeply in the process of learning, they were worked with a group project throughout the semester and they were asked to apply

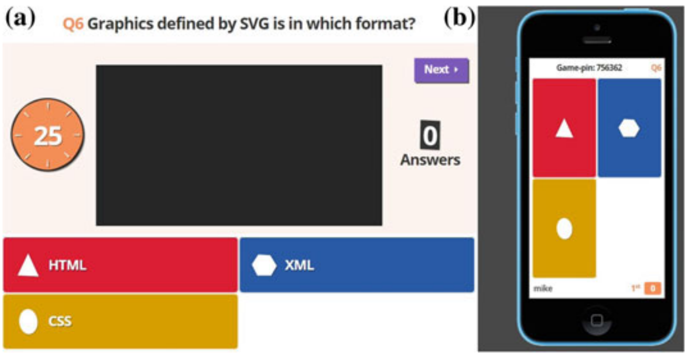

Fig. 12.3 An example question by the clicker: projected question (**a**); students' mobile (**b**)

the obtained knowledge as well as to make pertinence to their project presentation. This gave them the opportunity to be involved in an active learning process. The aim was to engage students more deeply in the process of learning course material by encouraging critical thinking and fostering the development of self-directed learning. Active learning affords the opportunity for application and practice and the asking of questions.

12.3 Early Results

An initial empirical validation of the proposed framework took place in a public university. The goal of this empirical validation is to provide the first analytics-based evidence regarding the effectiveness and acceptability of the proposed framework. The early results should not be seen as a rigorous evaluation of the proposed framework, but as reflections rising from a particular case study as well as empirical evidence for the further development of the framework.

12.3.1 Sampling

In the empirical evaluation, 170 computer science majors (20–29 years of age, 34 females and 136 males) were enrolled in the Web technology course. The seminar lasted 12 weeks, and we applied the proposed framework (as described in Sect. 12.2.2). In addition to students' analytics obtained from the aforementioned systems, we employed a post-survey. A total of 37 students (21.8 %) volunteered to participate on the survey (4 females, 33 males, with a mean age 22.95 and SD 2.86).

12.3.2 Measures

In order to be able to portray students' experience during the course, we employed three different types of measures.

(a) *Students' video navigation* (collected via video learning analytics system).
(b) *Students' learning performance/score* (collected via the quizzes), and
(c) *Students' attitudes toward the course* (collected via the post-survey).

In particular, video navigation was captured based on students' integration with the video player. Students' learning performance was collected in pre-, mid-, and post-measures throughout the semester. At the end of the course, we also used a post-attitudinal survey. The survey included measures of (1) ease, (2) control over the course, (3) intention to participate in similarly made course, and (4) usefulness of the overall teaching approach. Table 12.1 lists the operational definitions, the

Table 12.1 The measures and its definitions

Construct[a]	Definition	# of quest[a]	Source
Easy	The degree to which a student believes that the teaching approach of the course was easy for him/her	3	[11]
Control	The degree to which a student perceives how easy or difficult it would be to perform an operation in the course	3	[7]
Intention to participate	The degree of students' intention to participate in similarly developed courses in the future	4	[12]
Usefulness	The degree to which an individual believes that this teaching approach is useful	3	[11]

[a]Mean values of the questions were used for the analysis

number of items (questions) of each of the constructs (measures), as well as the source from which the measures were adopted. We employed a 7-point Likert scale anchored from 1 ("completely disagree") to 7 ("completely agree").

12.3.3 Statistical Analysis

As aforementioned, the collected data consist of three different types; therefore, an appropriate data analysis was used for each different set of data. As per students' video navigation, we used the aggregated time series visualization, in order to identify students' navigation throughout the video lecture and the importance of having a concrete assignment alongside with the video lecture.

As per students' learning performance, we captured students' pre-, mid-, and post-assessment scores, mapped them in a diagram, and employed an analysis of variance (ANOVA), and this will allow us not only to capture students' performance toward the course, but also to identify any potential shift during the course. Last but not least we used descriptive statistics on students' attitudes toward the course.

12.3.4 Results

With the visualization of the students' activity using graphs, we reach the conclusion that the quiz associated with the video assignments provide an important motivation for students to watch the videos and be prepared for the at-class activity. As we can see from Fig. 12.4, most of the students stopped the video after reaching into the segment where the information for the last question was found. On the other hand, the "attractive" (many views) video segments were identified at the video segments where the presenter was giving the solution of the respective problem.

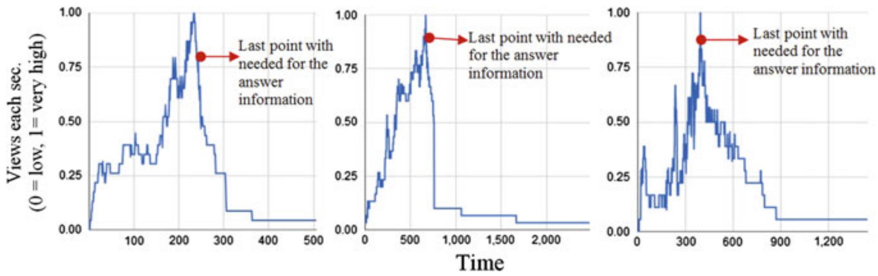

Fig. 12.4 Students' activity graphs, identifying students' dropout after finding the response of the last question of the assignment

To examine any potential shift in students' performance during the course, we used ANOVA between the pre-, mid-, and post-scores. As we can see from Table 12.2, students' scores were at very high levels in the pre-, mid-, and post-assessment. Performing an ANOVA, the results showed no significant difference (Table 12.2). As a consequence, there was no shift in students' score throughout the course.

Regarding students' attitudes toward the approach, we used an attitudinal survey to assess them (Table 12.1). We proceed to test the reliability of each measure using Cronbach α coefficient (Fig. 12.5). The result of the test revealed acceptable indices of reliability in all the factors (>0.7). We also computed descriptive statistics for the factors under investigation. Students expressed high degree of control (6.39/7) over the course, and somewhat lower (though still very high) level on the intention to participate (5.87/7) in similarly developed course in the future. In addition, students rated very high the easiness of following the processes (5.79/7) of the video course and the usefulness of this teaching approach (5.53/7). High levels of these constructs indicate positive views concerning usability, control, and usefulness of the proposed approach.

Table 12.2 Students' learning performance in pre-, mid-, and post-assessments

	Mean (SD)			*F* (*p*)
	Pre-assessment	Mid-assessment	Post-assessment	
Learning performance	7.59 (1.46)	7.99 (1.82)	7.94 (1.86)	0.980 (0.378)

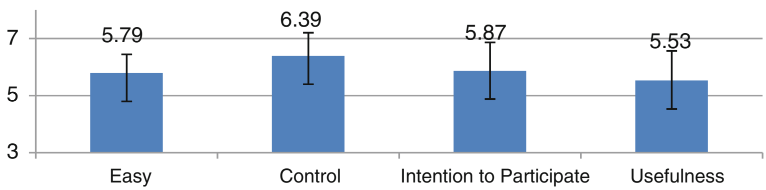

Fig. 12.5 Student's attitudes toward the approach

12.4 Discussion and Conclusions

Practical principles and heuristic models that enable actors within the learning ecosystem to understand and shape their learning future are considered as one of the cornerstones of smart learning environments [13]. In this research, we presented a learning ecosystem framework and the first captured results of its application. The framework can be put into practice using basic e-learning tools and active learning practices; hence, the framework can be used for those interested in incorporating flipped classroom in their teaching, since it is a flexible procedure that may be adapted to meet different needs.

By exploring the notion of learning ecosystem, we shown that it is applicable to describe and model the main actors, diverse resources, and sociotechnical dynamics within learning. Hence, the concept of ecosystem is an interesting approach which can be applied in learning and gives an overview of the different roles, processed as well as learning dynamics.

The proposed framework was also applied in a second-year course, named "Web technologies." In the empirical study, we investigated students' content navigation, learning performance, and attitudes. We also indicated that the main quality of the "attractive" information video segments is the rich and useful amount of transferred information and knowledge and of course its association with students' assessment. Last but not least, we presented students' progress throughout the course using pre-, mid-, and post-assessment and examined their attitudes regarding easiness, usability, usefulness, and acceptance of the course.

We want to emphasize that our findings are clearly preliminary with inevitable limitations. As for the internal validity of the empirical study, data are based on a self-reported method, log files, and assessments. Other in-depth methods such as semi-structured interviews could provide a complementary picture of the findings through data triangulation. As for external validity, the subjects were computer science majors, which may somewhat limit the generalizability of our results. Nevertheless, the insights drawn are not connected with the subjects' background and can be applied on any population.

Another direction of research is to apply the framework proposed in this paper to the investigation of existing highly engaging learning practices, such as peer instruction and inquiry-based pedagogy. Our future research will concentrate on further refinement of the proposed framework by applying and evaluating it on classes of larger scale and different topics. Further research will also inform the development and evaluation of e-learning environments to better support active learning and livable and sociable learning spaces [13]. This study can provide a springboard for other scholars and practitioners to further examine the efficacy of this specific approach to learning, since it is an established flexible procedure that can be used and adapted to meet the needs of those interested in using the flipped classroom approach.

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Chapter 13
Historical Overview of Adaptive e-learning Approaches Focusing on the Underlying Pedagogy

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Abstract This paper attempts a historical overview of adaptive e-learning approaches through the lens of a well-known categorization, which distinguishes among the macro-adaptive approach, the aptitude–treatment interaction approach, the micro-adaptive approach, and the constructivist–collaborative approach. Early and more recent examples in each category are presented in order to conclude on similarities and differences among the approaches. The history of adaptive e-learning systems is discussed, and the main conclusion drawn is that, historically, the development of adaptive e-learning systems has followed the trends of education and cognitive science.

Keywords Macro-adaptive approach · Micro-adaptive approach · Aptitude–treatment interaction approach · Constructivist–collaborative approach

13.1 Introduction

A decade ago, mass individualization in education and in training communities was the "next big thing." Today, it is generally accepted that the students' performance can be improved through adaptive e-learning environments that suit their needs [1]. This paper discusses the affordances and the constraints of adaptive e-learning systems through a comprehensive description of the most prominent underlying approaches. Next, examples of various adaptive e-learning systems are presented along with a short description of their pedagogical components. The paper concludes on the differences and similarities among the approaches and critically discusses the history of adaptive e-learning systems.

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13.2 Categorization of Adaptive (e-)Learning Approaches

The macro-adaptive approach addresses adaptation by allowing different alternatives for the selection of learning objectives, curriculum content, and delivery systems, based on the student profile and characteristics. These characteristics are as follows: cognitive or learning styles, student's learning goals, delivery systems, achievement levels, levels of detail, etc [2, 3]. These characteristics affect the adaptive e-learning systems in different ways, such as diagnosing the learner's specific learning needs and providing instructional prescriptions for them [1], defining preconditions for learning content, adapting to the students' learning styles, and achieving different types of learning objectives in accordance with the individual student needs or abilities [3]. Pre-planned adaptive e-learning strategies are then created by the experts for the various categories of learners [4].

The aptitude–treatment interaction (ATI) approach "suggests different types of instruction and/or different types of media for different students" (p. 5757) [2], and it is based on the idea that if learner aptitudes are paired with the right treatments, prediction of learning outcomes would be more effective. The aim of the ATI approach is to find linkages between learning and aptitudes [3]. To this end, one aspect of the ATI approach deals with the locus of control on the learning process, e.g., it is more effective to limit the control for students with low levels of prior knowledge [3]. Classes of aptitudes in the ATI research identified by several studies [3, 5] include intellectual abilities (such as reasoning ability and mathematical ability), cognitive or learning styles, and (prior) student knowledge [5]. Also, metacognitive abilities are considered important in the ATI approach, and researchers study their impact to variables such as the feedback and the control [2]. Recently, researchers recognized cognitive processing capacity as an influencing aptitude; thus, new adaptive e-learning systems that incorporate implications of cognitive load theory into their design have been developed.

The micro-adaptive approach diagnoses student's specific learning needs during instruction and consequently provides suitable instructional prescriptions and tactics for these needs [3]. That is, micro-adaptive instructional models rely mostly on on-task rather than pre-task measures. Intelligent tutoring systems (ITSs) are an example of this approach. In the case of macro-adaptive instruction, the differentiation of teaching operations is frequently used over larger segments of instruction [3]. On the contrary, a micro-adaptive model uses the temporal nature of learner abilities and characteristics, especially the dynamically changing ones, such as affective states, response errors, and response latencies. Monitoring the user's behavior and performance can be used for optimizing instructional prescriptions (such as treatments and sequences) on a refined scale [6]. Most micro-adaptive models adjust learning content (structure, presentation, amount) during instruction on the basis of a quantitative representation of learner traits.

In addition to the ones mentioned above, some researchers (e.g., [2, 3] also suggest another approach, the constructivist–collaborative approach. As its name implies, this approach supports constructivist learning by incorporating in the design suitable mechanisms of knowledge representation, reasoning, and decision making and/or collaboration through adaptive grouping. Computer-supported collaborative learning has been supported by Web 2.0 tools and social media in adaptive e-learning. In the Open Discovery Space project, the formation of online communities of learning among teachers is also enabled though user ratings and recommendations.

13.3 Examples of Adaptive (e-)Learning Systems

Examples of systems that support the macro-adaptive approach are given as follows: The macro-adaptive is the oldest of the four already mentioned approaches [7]. Early macro-adaptive examples of adaptive learning systems (pre-World War II) are the "Individual Learning Plans" (ILPs), the Dalton Plan and the Winnetka Plan. The ILPs triggered a school of thought in the American education which stimulated moving from the traditional teacher-led instruction to individualized learning. During the 1960s and 1970s refinements in task analysis procedures, the emergence of criterion reference testing and Gagne's theory of learning hierarchies probably affected the development of individualized instruction systems. The first computer system of technology-enhanced learning (TEL) was Programmed Logic for Automated Teaching Operations (PLATO). Developed in the 1960s and 1970s, PLATO is regarded as one of the most successful systems in the history of TEL [8]. The Plato Learning Management System, an evolution of the original PLATO system, could provide some rudimental adaptation: When mastery of all objectives in the module was reached, the student could proceed to the next module. The first system intentionally designed for adaptive instruction was, developed by Ross and Morisson, incorporated the prediction of student learning needs; however, these needs could be only diagnosed in the pre-instructional phase, not during instruction. In addition to these macro-adaptive characteristics, this system also combined some features related to the micro-adaptive approach. The adaptive e-learning system, a recent example of macro-adaptation described in [9], presents learning materials that match students' learning styles, either globally or sequentially. The system identifies the student's learning styles tendency through questionnaire. The system is implemented by customizing the Moodle Learning Management System.

Examples of systems that support the ATI approach are given as follows: Carrier and Jonassen [10] proposed an eight-step model to provide practical guidance for applying the ATI model to the design of courseware which actually resembled the Dick & Carey's instructional design model. In addition, they suggested four adaptation methods based on conceptual mappings between instructional strategies and student characteristics: (a) remedial actions for providing supplementary instruction; (b) capitalization/preferential actions, for providing instruction in a manner consistent with a student's preferred mode of perceiving or reasoning; (c) compensatory, for supplanting some processing requirements of the learning task (e.g., cognitive processing capacity); and (d) challenge, for motivating students to use and develop new processing modes. Park and Lee [11] argued that although it seems that this model has high practical value, "without theoretically coherent and empirically traceable links among different learner variables and without clearly defined types and levels of learning requirements and instructional strategies for different tasks, the mere application of this model is not likely to produce better results than those of non-adaptive instructional systems," (p. 472) something which it is obvious.

One of the latest trends regarding the ATI approach is focused toward learner's cognitive load as an adaptation parameter. For example, e-TPCK [6] is an adaptive e-learning system, which has been designed and developed specifically for promoting teachers' ongoing advancement of knowledge on how to teach a particular topic using specific ICT tools. It is emphasized that e-TPCK was designed to be a cognitive partner for scaffolding teachers' learning by personalizing the content presented to them in the form of ICT-infused design scenarios. Among others, the system pertains to adaptive design scenario selection with shared control between the user and the system based and the learning path of its users based on ratings of their perceived mental effort about the design scenario presented to them.

Examples of system that support the micro-adaptive approach are given as follows: Early examples for the micro-adaptive approach are based on programmed instruction, and most recent models apply artificial intelligence techniques [5]. In Kickmeier-Rust et al. [12], micro-adaptivity enabled monitoring and interpretation of the learner's behavior in a game's virtual world, namely ELEKTRA, by personalizing the provided guidance and feedback in a meaningful way which was embedded in the game's flow without corrupting immersion or the flow of the game experience. Micro-adaptivity was used to interpret the learner's problem-solving behavior in a way that was consistent with the idea of gaming. To this end, the respective domain model included competence states, problem states, and possible learning paths.

In the ALICE digital storytelling project [13], the proposed model exploited a branching logic approach to (a) design micro-adaptivity in the digital story exploiting information derived from assessment results and (b) define remedial learning paths. The model enabled linking pre-scripted alternative routes to direct learners to remedial paths. These paths facilitated support and motivated learners to achieve the learning objectives. Role assignment was another level of micro-adaptivity. The rationale was that changing the role of a learner may modify the viewpoint by which (s)he interacted with the story and the didactic value of the story. The affective dimension was an additional variable integrated in the adaptation model to create an emotional storytelling by keeping track of the user's expected emotional state.

Examples of systems that support the constructivist–collaborative approach are given as follows: Examples of systems that support this approach incorporate motivational factors in their design or collaborative activities. For example, the COSMO system included a life-like animated pedagogical agent whose facial expression, tone of voice, gesture, etc., were dynamically changing in response to its interactions with learners [14]. Also, this approach included systems that fostered self-regulated learning or students' metacognitive abilities. Cognitive Tutor [15] is an intelligent tutoring system created by a research team from the Carnegie Mellon University that offers adaptive problem-solving support in two forms, on demand and just-in-time contextual hints, in multiple levels of detail according the student's specific goal within the problem at hand. The goal of the system is to recognize and increase the students' metacognitive abilities and in particular, their help-seeking behavior [16]. Choi and Kang [10] presented an adaptive e-learning system which supported location-based collaborative learning using semantic modeling and GPS sensors. In particular, a social network among learners was dynamically constructed based on information about the learners' location and helped learners to find mentors to facilitate their learning and to create communities of learning.

13.4 Discussion

Adaptive e-learning systems are not put in mutually exclusive classes in this categorization [4]. Inspection of the literature has indicated the following differences among them: (a) The ATI approach is very closely related to the macro-adaptive approach in that it focuses on adapting instructional tactics to individual learner characteristics and differences [4]. Contrary to the macro-adaptive instruction which always tailors instruction before training begins, the ATI approach can also be used to adapt the instruction during training [4], (b) contrary to macro-adaptive models which use relatively stable characteristics (such as cognitive style) to define which instructional tactics are most appropriate in a given situation, micro-adaptive models are dynamic and use within-task measures or temporal learner characteristics (such as motivation level), and (c) in contrast with micro-adaptation, macro-adaptive decisions are domain-independent [17]. In the case of content adaptation, what to present is a micro-adaptative decision, and how to best present it is a macro-adaptive decision.

It seems that the development of adaptive e-learning systems historically follows the philosophical underpinnings of education: behaviorism, cognitivism, and constructivism. Early research on adaptive e-learning is based on behaviorist approaches, mostly on programmed instruction, in which the instructional materials are divided into associated units of learning. Learning the previous unit is a prerequisite for continuing to the next one, and all units are connected sequentially. Later on, adaptive e-learning and its implementations were affected by cognitivist approaches, and in more recent years, while the two other approaches (programmed instruction, information processing theory) are not abandoned in the adaptive e-learning field but revisited, systems that enable collaborative learning, mobile learning, and motivational competence and shared control of the adaptation process between the system and the learner have begun to attract the attention of the research community.

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Chapter 14
Using the Hybrid Social Learning Network to Explore Concepts, Practices, Designs and Smart Services for Networked Professional Learning

John Cook, Tobias Ley, Ronald Maier, Yishay Mor, Patricia Santos, Elisabeth Lex, Sebastian Dennerlein, Christoph Trattner and Debbie Holley

Abstract In this paper, we define the notion of the Hybrid Social Learning Network. We propose mechanisms for interlinking and enhancing both the practice of professional learning and theories on informal learning. Our approach shows how we employ empirical and design work and a Participatory Pattern Workshop to move from (kernel) theories via Design Principles and prototypes to social machines articulating the notion of a HSLN. We illustrate this approach with the example of Help Seeking for healthcare professionals.

Keywords Smart learning environments · Post-Vygotskian theory · Work-based group collaboration · Social machines · Smart services · Design Principles

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14.1 Introduction

This paper considers the design of technology to support informal learning in hybrid networks of professionals. This design aims to reflect an innovative pedagogy, grounded in practice and supported by theory, and enables the fusion of the technology and the pedagogy to transform professional practice. In this paper, we define the notion of Hybrid Social Learning Network (HSLN), a 'conceptual framework for smart (informal) learning environments,' and propose mechanisms for interlinking and enhancing both the practice of professional learning and theories on informal learning.

The research reported in this paper has been influenced by Daniels' argument [1, p. 1] that 'Vygotsky and his followers provide a rich and vivid palette of theoretical and methodological ideas which can be utilized as we struggle to understand the process through which the human mind is formed.' In a similar vein, the conceptual work reported should be viewed as descriptive and experimental research and is being used here to make conceptual distinctions and organize ideas about 'hybridity in networked professional learning'; Vygotsky and those who have been influenced by him are used as sources to provide us with the appropriate ideas to assist this undertaking. This paper describes HSLN, a concept that has emerged from an extensive critical literature review and earlier co-design work (e.g., see [2]) as part of the Learning Layers Project (http://learning-layers.eu/). The paper attempts to reconcile post-Vygotskian theory (and particularly recent cultural-historical work on hybridity) with the core idea of social machines, the '50-50 partnership' between people and machine in order to design technology that fits with working and learning practices, in our case of healthcare professionals.

14.2 The Hybrid Social Learning Network

Social learning refers to a wide range of cultural-historical processes and practices where learners make use of social interactions to construct meanings and change behavior [1]. *Networked learning* is defined as 'learning in which ICT is used to

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promote connections: between one learner and other learners; between learners and tutors; between a learning community and its learning resources' [3]. We extend the notions of 'social learning' and 'networked learning' by the concept of hybridity. For us, hybridity in professional learning has two dimensions: (i) a hybrid combination of formal and informal social structures in an activity system, i.e., the professional role we adopt or are positioned into in terms of structural relations of the power and control in institutional and cross-institutional settings [1, pp. 148–178] and (ii) a hybrid combination of physical and digital tools; how cultural historically developed tools (physical and digital) mediate the individual's relation to the world where the competence to handle such tools is acquired in social settings through guidance from other persons or guidance from digital tools in a '50-50 partnership' [4]. In other words, people connect and interact through a hybrid network of physical and technology-mediated encounters to co-construct knowledge and effectively engage in positioning practices necessary for their work. In our vision, professional learning will be transformed by introducing tools which are designed for this HSLN mode of mediated learning. We suggest professionals learn from each other in groups (a Zone) that call for orchestrating social supports (navigation and bridging aids) so that learners can benefit from the ideas of others (Possibility). The HSLN can thus be seen as a framework for enabling a 'Zone of Possibility' [1, p. 164].

The concept of Hybrid Social Learning Network is being used here to make conceptual distinctions and organize ideas so that we can design concepts, tools, and services for professionals, in our case healthcare sector workers, enabling them to work collaboratively in groups and ask questions to people, networks and services that they trust. The Social Semantic Server or SSS [5] is the technological framework providing tools and associated users with a growing set of services of different granularities that generate and utilize social and artifact network data needed in a HSLN. We employ services that recommend relevant conversations, documents, and other resources from a person's wider hybrid network that allows them to build, maintain, and extend their network to support workplace learning. In doing so, we face a dual design challenge: (i) the design and technology need to fit with working and learning practices of a target group (e.g., healthcare professionals) and (ii) the technical development fits with our theoretical orientation of cultural-historical practice.

Shadbolt et al. [4] put forward the notion of the 'social machine' as an ecosystem that blurs the lines between computational processes and input from humans and describe a polyarchy (defined as hierarchy with multiple entity points) used to identify 'the polyarchical relationship between infrastructure, social machines, and large-scale social initiatives.' Consequently, we wondered how the 'theory' and 'design considerations' components that we are interested in could be brought into the polyarchy without destroying the original idea of Shadbolt of 'nested models of social machines' and while retaining recognition of the fact that theory is actually also constructed on different levels of abstraction in itself. So for us, there needs to be an unpacking of the theory and design that form the lowest level of the polyarchy, i.e., what Shadbolt et al. call the 'initiative' level.

In conceptualizing a theory-driven design of recommender systems, Arazy et al. [6] speak of a similar idea in that they separate a 'kernel theory' on the highest level of abstraction which is broken down to an 'applied behavioral theory' which is then turned into testable designs. This conceptualization, however, construes the relationship between theory and design as a one-way street (theory-driven design). Furthermore, in our understanding, Shadbolt et al.'s description is analytical, while Arazy et al.'s is prescriptive. Shadbolt et al. describe the current workings of socio-technical systems, and Arazy et al. describe a process for constructing tools. In contrast, we aim to give an equal weight to theory and practice. For us, design constructs mediate between theory and practice, constantly (re)shaped and (re) shaping both. Consequently, we have decided to conceptualize the top three layers of the social machine (infrastructure, frameworks, and services, all grouped on the right of Fig. 14.1) and their relations to theory and models to inform an 'initiative' or the bottom level of the social machine polyarchy (grouped at the top of Fig. 14.1). The design research cycle (grouped on the bottom left of Fig. 14.1), then, prescribes how to build an 'initiative.'

Figure 14.1 shows the HSLN with pathways that we have, or intend to, follow(ed) illustrating how we use this 'conceptual framework for smart (informal) learning environments' to drive the development of an 'initiative,' where the focus is on maintaining a fit with our kernel theories and on the use of recommender systems that can adaptively scaffold learners for supporting informal learning. The sequence

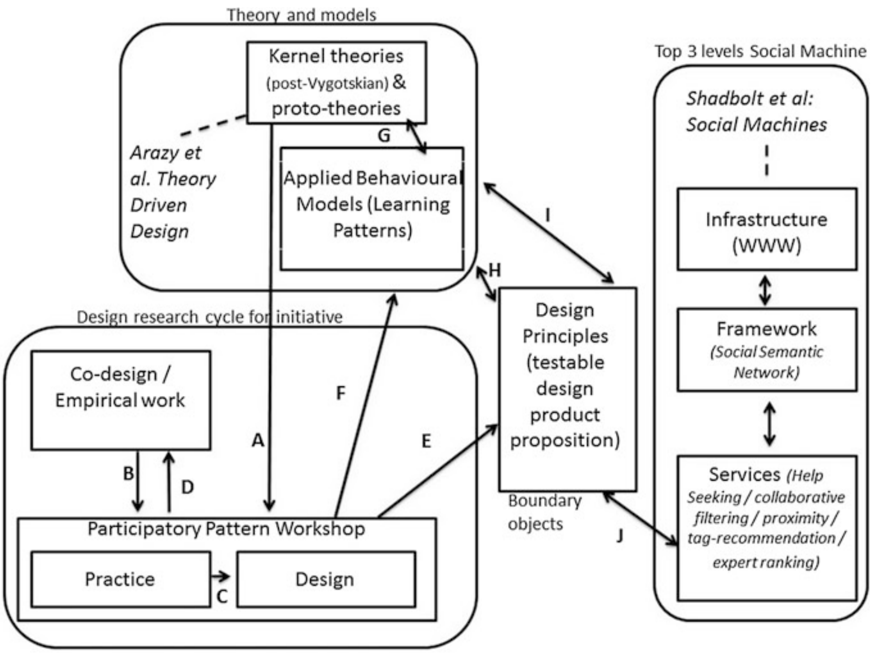

Fig. 14.1 Hybrid Social Learning Network: the paths followed

in Fig. 14.1 represents how we investigate which services (in a technical sense) are needed to enable us to realize tools thus articulating a HSLN; loops are indicated by arrows going in both directions. Path A from kernel theory and proto-theories (theories in progress) represents meta-requirements elaborated upon in the Participatory Pattern Workshops (PPW) that incorporate full theories, e.g., more capable peer [7], and proto-theories, e.g., '50-50 partnership' [4]. Vygotsky [7] describes how a range of skills could be performed with the assistance of a 'more capable peer': experienced peers who can assist in developing the person's skills, which cannot yet perform independently.

Earlier project co-design findings are added into the PPW (path B; e.g., we work with Practice Nurses based in UK General Practitioner clinics and found they were setting up a new face-to-face network because most of the nurses work in a single-handed manner at their practices, thus leading to isolation from similar colleagues; face-to-face meetings had the problem of variable attendance and that there is little communication by e-mail). We extended the PPW methodology [8] for the co-construction of design knowledge (path C and box in the bottom left of Fig. 14.1) by adding an emphasis on meticulous analysis of current practice. We first specify what the change in practice is that we wish to engender. This will be the objective of our design and the measure of its success. Design scenarios are proposed solutions to identified problems (path D where scenarios are used in more co-design; for the Practice Nurses network described above the main scenario was tools to expand their group, improve their sharing practices, and explore the potential for mentoring within the network). Design Principles (path E) are imperatives for design, derived from theory and validated empirically that act as boundary objects to drive designs of our tools and may also influence the choice of kernel theories that are employed (path F; e.g., participants argued for a stronger inclusion of communities of practice theory in the PPW workshops in February 2015). There are also paths connecting to the applied behavioral model: the links between kernel and applied behavioral model (path G) and between theory and Design Principles (path H; testable Design Principles may also apply some constraints on the development of the applied behavioral model of seeking help and recommendations). Path I shows how our planned evaluations will feed back to theory and model. Scaffolding is where effective answers emerge from the connection between peers and experts, and 'System Scaffolding' is where contextualized information will be delivered by technology. This combination is what we call the '50-50 partnership.' Path J is where we match the development of services and Design Principles. Specifically, we showcase a question/answer feature for Help Seeking in the KnowBrain tool [9], shown in Fig. 14.2, an open-source knowledge repository with smart social and collaborative learning features for informal workplace learning. KnowBrain's multimedia question–answer feature offers two kinds of realizations of the concept of the more capable peer for scaffolding a learner who is seeking help that articulates the concept of a 50-50 partnership: (i) More experienced human learners or experts can take the role of more capable peer in answering the stated questions in the form of text-based answers or via the provision of appropriate documents, media objects, or links; (ii) a recommender can take the role of more capable peer in suggesting

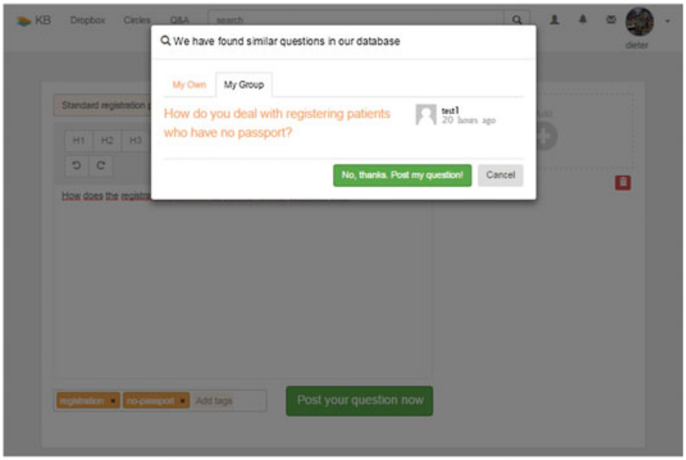

Fig. 14.2 Example of KnowBrain

preexisting questions about the topic of inquiry, i.e., when a new question is stated, similar preexisting questions are suggested first so that the learner can take them as a starting point and extend them with new and up-to-date knowledge (Fig. 14.2). If the preexisting answers are not sufficient, the learner can also discover more capable human peers who previously engaged in the same topic of interest. Finally, when we test our design products, we move them into 'live' systems (path J plus the right-hand side of Fig. 14.1, e.g., tools to support Help Seeking comprise bundles of services that use the SSS as backend).

14.3 Conclusion

This paper has provided details of a rigorous approach within which we investigate mechanisms for interlinking practice and theory to inform and enhance both. Our approach shows how we employ empirical and design work and a Participatory Pattern Workshop to move from (kernel) theories via Design Principles and prototypes to social machines articulating the notion of a HSLN. It offers a powerful explanatory frame and step-by-step guidance of the functioning and scope for learning in hybrid professional networks. In future work, we will test the impact of our tools on practice toward more effective social learning at the workplace and we will examine how HSLN supports multiple or extended learning theories. For example, Vygotsky focused more upon Culture as providing tools for thinking as a mechanism for collective problem solving. With this concern in mind, the following research question is guiding new work aimed at extending the notion of more capable peer: *Is there evidence of the 'power and authority' issue and how does social discourse involve positioning and being positioned?*

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Chapter 15
Quantitative Analysis of Newcomer Integration in MMORPG Communities

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Abstract Players of massively multiplayer online role-playing games (MMORPGs) build online knowledge communities that can serve as learning environments for informal adult learning. Technologies that can make these communities "smart" require quantitative models of specific processes. Aiming to inform the development of smart technologies for MMORPGs, the present research proposes and validates questionnaire survey scales that quantitatively explore the process of newcomer integration in German MMORPG player communities. Two correlational studies within samples with a total of N = 276 participants reveal players' perceptions of recruiting strategies, monitoring, and consistent training, influenced by gender, age, and community exposure time. These perceptions, in turn, significantly impact players' subjective competence, sense of community, and evaluations of community practice. The findings make headway in smart community research by suggesting quantitative models for social processes in MMORPG communities.

Keywords Knowledge communities · Massively multiplayer online role-playing games (MMORPGs) communities · Newcomer integration strategy

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15.1 Introduction

Knowledge communities (KCs) are groups of mutually engaged people communicating online over longer periods of time and sharing interests, knowledge, and activities. Research points at KCs, either online or traditional, as particularly effective environments for informal adult learning [1, 2]. KCs are characterized by their sociocognitive structure that includes central, active, and peripheral members [2]. A particular case of KCs are online knowledge communities (OKCs) built by players of massively multiplayer online role-playing games (MMORPGs) [3] that display similar sociocognitive structures, processes, and outcomes such as traditional KCs. Identity within KCs typically develops from newcomer and novice to old-timer and expert. The participation outcomes in KCs include the acquisition of skills and applicable knowledge [1, 2], participants' positive self-evaluation and development toward expert status [2, 4], and the emergence of a sense of community [5].

Eberle et al. [6] explored the participation support structures for newcomers in faculty student councils and found out that newcomer integration may be the purpose of *recruitment strategies*, which in turn may be backed by the *accessibility of community knowledge*. *Positive welcome strategies,* which are a newcomers' first contact with the community, are meant to foster their gratefulness toward the community and their interest to acquire specific community knowledge. *Negative welcoming strategies* are initiations confronting newcomers with their own shortcomings, which aim to show them the need to attain a higher level of knowledge and skills to become full community members. Nevertheless, a community will recognize the need to attract newcomers (*legitimation*) and offer them *opportunities for participation*. Senior community members may offer *role models* by showing newcomers how to behave according to community norms; explicitly *train* newcomers in the community practice; *sponsor* them by serving as a contact person; and *encapsulate* them by encouraging newcomers to spend time dedicated to the team and in separation from potentially distracting influences. Welcoming and training strategies are usually complemented by *monitoring newcomer behavior* and *assessing* their *knowledge* about the community and its practice. Eberle et al. [6] empirically demonstrate that two specific participation support structures, the recruitment strategies and the accessibility of community knowledge, predict newcomers' level of participation.

Newer technologies can make OKCs "smart," e.g., by automatically analyzing typical processes and thus predicting future learning or social behavior or informing certain interventions [7]. So far, little is known about newcomer integration in KCs, and especially in OKCs. Therefore, the present research starts from one of the few quantitative studies exploring newcomer integration in KCs, proposed by Eberle and colleagues [6], and extends it to MMORPG communities. The findings add to current research on smart communities [7].

15.2 Research Questions, Methodology, and Findings

Against the background of the provided theoretical considerations, the following research questions were formulated: (1) Which newcomer integration strategies do players perceive in their MMORPG community? How far are these impacted by demographic data, in particular by gender, age, and community exposure? (2) What are the effects of perceived newcomer integration strategies on participants' subjective community outcome?

Two quantitative, correlational, survey-based studies were conducted in different player communities. In Study 1, newcomer integration strategies were searched for by scales derived from the definitions provided in the theoretical framework [6]: the *recruitment strategies* scale (e.g., "In our players community, I actively search for new players with whom I can play"); the *negative welcome strategies* scale (e.g., "Newcomers have to go through a difficult initiation ritual before they are accepted"); the *consistent training* scale (e.g., "Our players community offers a kind of regular training for newcomers"); the *modeling* scale (e.g., "I am always to behave as an example for newcomers"); the *monitoring* scale (e.g., "I always look very carefully at new players before I play together with them"); the *integration strategy evaluation* scale (e.g., "I am happy with the way in which our player community recruits new members"); and the *self-evaluation of player competence* scale (e.g., "I am one of the best players in our community"). Additionally, community output was assessed as *sense of community* with a *social* and a *learning* component [5]. All scales consisted of statements that had to be rated using seven-point Likert scales from 1 = very weak to 7 = very strong perceptions.

Study 1 was conducted in a MMORPG community of approx. 500 German players of the game "Guild Wars 2." The participant sample consisted of $N = 123$ players, 106 male and 16 female, aged on average $M = 25.12$ years (SD = 8.19).

RQ1. The results displayed moderate values of the following perceived recruitment strategies: *consistent training, modeling,* and *monitoring;* low values of *negative welcome strategies*; and high values of *sense of community*.

Male players perceived integration strategies more strongly than female players, which was true for *monitoring* (male: $M = 3.55$, SD = 1.64; female: $M = 2.64$, SD = 1.16; $F(1, 119) = 4.534$, $p < 0.05$); *negative welcome strategies* (male: $M = 2.23$, SD = 1.14; female $M = 1.64$, SD = 0.55; $F(1, 120) = 4.083$, $p = 0.05$, marginally significant); *recruitment strategies* (male: $M = 3.28$, SD = 1.74; female: $M = 2.40$, SD = 1.06; $F(1, 120) = 3.904$, $p = 0.05$, marginally significant); and *consistent training* (male: $M = 5.80$, SD = 0.95; female: $M = 5.31$, SD = 1.07; $F(1, 120) = 3.574$, $p = 0.06$, marginally significant). No significant gender differences in modeling or in both components of the sense of community scale. Participants' *age* had very weak, negative effects on *monitoring* ($r = -0.28$, $p < 0.01$, $R^2 = 0.07$), *recruitment* ($r = -0.23$, $p < 0.05$, $R^2 = 0.04$), and *consistent training* ($r = -0.19$, $p < 0.05$, $R^2 = 0.03$).

RQ2. No significant effects of perceived integration strategies on any component of sense of community could be detected. *Community exposure* had weak, negative effects on *consistent training* ($r = -0.21$, $p < 0.05$, $R^2 = 0.04$) and *sense of community (learning)* ($r = -0.19$, $p < 0.05$, $R^2 = 0.03$). Due to the very small cleared variance, these effects can hardly be considered as significant.

As a follow-up, **Study 2** was performed in various German player communities built on several games such as "Guild Wars 2" and "World of Warcraft". The sample was demographically similar to Study 1 and consisted of $N = 153$ players, 123 male and 30 female.

RQ1. The newcomer integration strategies *recruitment*, *consistent training,* and *monitoring* were moderately perceived. High values were measured in the *integration strategy evaluation*. *Sense of community* was highly perceived.

Again, males perceive integration strategies stronger than females: *recruitment strategies* (male: $M = 5.17$, SD = 1.04; female: $M = 4.12$, SD = 1.12; $F(1, 151) = 26.380$, $p < 0.000$); *monitoring* (male: $M = 3.64$, SD = 1.17; female: $M = 2.88$, SD = 1.21; $F(1, 151) = 14.074$, $p < 0.01$); and *consistent training* (male: $M = 5.00$, SD = 1.18; female: $M = 4.58$, SD = 0.86; $F(1, 151) = 3.493$, $p = 0.06$, marginally significant). No significant gender differences were found in *modeling* and in both components of the *sense of community* scale. Participants' *age* had very weak, negative effects on *monitoring* ($r = -0.18$, $p < 0.05$, $R^2 = 0.03$), and no significant effects on recruitment strategies and consistent training.

RQ2. Participants' *integration strategy evaluation* was influenced by *consistent training* ($\beta = 0.33$, $p < 0.01$) and *monitoring* ($\beta = -0.20$, $p < 0.05$), which cleared $R^2 = 0.10$ of the variance. Recruitment strategies had no significant effects.

The *social* component of *sense of community* was significantly impacted by *consistent training* ($\beta = 0.46$, $p < 0.000$) and *monitoring* ($\beta = -0.23$, $p < 0.01$) and marginally by *recruitment strategies* ($\beta = 0.16$, $p < 0.10$), clearing altogether $R^2 = 0.26$ of the variance. Further on, *consistent training* had a moderate effect ($\beta = 0.47$, $p < 0.000$) on the *learning* component of *sense of community*, clearing $R^2 = 0.28$ of the variance. Recruitment strategies and monitoring had no significant effects.

Participants' *subjective competence* was strongly predicted by *consistent training* ($\beta = 0.53$, $p < 0.000$) and *recruitment strategies* ($\beta = 0.25$, $p < 0.01$), which cleared $R^2 = 0.46$ of the total variance. Monitoring had no significant effects.

Finally, *community exposure time* had significant effects on *subjective competence* ($r = 0.43$, $p < 0.000$, $R^2 = 0.18$), *sense of community (learning)* ($r = 0.39$, $p < 0.000$, $R^2 = 0.14$), and *sense of community (social)* ($r = 0.21$, $p < 0.01$, $R^2 = 0.04$).

15.3 Discussion and Conclusions

The presented research quantitatively explored newcomer integration in various MMORPG communities of German players. For the survey, a first version of integration strategies scale was formulated based on Eberle et al.'s study [6]. Only some of these scales proved reliable; therefore, the corresponding strategies were measured. Thus, the collected data successfully revealed players' perceptions of newcomer recruitment strategies, consistent training, and monitoring. Additionally, the first study also identified the perception of negative welcome strategies and modeling. A gender-specific pattern appeared, such that male players, who were the majority in the examined communities, more strongly perceived the newcomer integration strategies. Further, younger players perceived the newcomer integration strategies somewhat stronger than older players. This may be due to status differences [3], or simply to different perceptions of male versus female and younger versus older players. Direct observation data may reinforce this finding in future studies.

According to data from Study 2, consistent training seems to be the most important newcomer integration strategy, positively, and moderately to strongly impacting players' newcomer integration strategy evaluations, as well as their sense of community and subjective competence. Recruitment strategies only affected the social component of sense of community and the subjective competence, to a positive but relatively small amount. Monitoring had a negative effect on players' integration strategy evaluations and their social sense of community. These results emphasize the importance and positive effects of community strategies aimed at fostering members' expertise. Monitoring, on the other hand, may be indispensible for the individual and community development process; however, it seems to have negative social effects. The findings support the application of Eberle et al.'s [6] approaches in MMORPG communities. In future studies, objective data based on direct observation and discourse analysis [7] may additionally substantiate the findings.

Community exposure has relatively strong effects on players' subjective competence and sense of community, which suggests that these essential components of community output increase over time. This finding is consistent with the mainstream community research [2, 6]. However, it is limited by the subjective transversal data and has to be substantiated in future research by longitudinal data.

In consequence, these findings add to current research on MMORPG knowledge communities [3] and inform smart community research [7]. Follow-up studies are aimed to refine the data collection instruments and to add longitudinal, direct observation data.

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Chapter 16
Designing a Learning Recommender System by Incorporating Resource Association Analysis and Social Interaction Computing

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Abstract With the increasing growth of amount of learning resources in smart learning environment, it is quite challenging to find suitable resources and learning peers to cater for learners' different demands. This paper proposes a general architecture of learning recommender system for the smart learning environment. By constructing learner models and resource models, the proposed recommender system aims to recommend learning resources by using the clustering and association rule mining and to recommend peers via social interaction computing. Furthermore, the experiment on real datasets is conducted to demonstrate the effectiveness and usefulness of the approach.

Keywords Smart learning environment · Learning recommender system · Social interaction computing · Cluster analysis · Association rules

16.1 Introduction

With the popularity of the online learning, learners and their learning demands vary from person to person in learning communities. According to different learner's characteristics, how to provide learning resources and learning peer support services has been paid more and more attention. Meanwhile, with the explosive growth of network information and learning resources, learners face massive information and suffer "cognitive overload," "learning trek," and other issues. Under this situation, students often cannot effectively obtain useful knowledge and information.

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Recommender systems, one of the branches of online knowledge presentation and navigation, can dispose this problem. The researchers recommend learning resources using different recommend strategies [1–5]. Traditional resource recommends mostly used similarity matching of learner needs and resource attributions to recommend related resource to the learners. The effectiveness of system depends on that it can acquire the character of the learner in more detail. So, it cannot achieve better recommendation quality if learner information is sparse. Educational data mining has become an emerging research field used to extract knowledge and discover patterns from e-learning systems. Learning recommender system can become more effective based on the implicit knowledge and patterns in some situations that learner information can be acquired difficulty.

This paper proposes a learning recommender general architecture. By constructing learner models and resource models, the proposed recommender system aims to recommend learning resources by using the clustering and association rule mining and to recommend peers via social interaction computing.

16.2 The General Architecture of Recommender Systems

The architecture of the learning recommender system is illustrated in Fig. 16.1. And this architecture includes three parts: learner model, resource model, and data processing module. Data processing module is a core computing component. It includes clustering, association rule mining, and social interaction computing.

The learner model uses the following quadruple:

StuModel = (BasicInfo, Preference, LearnRecord, SocialInfo).

In this model, BasicInfo is basic personal information including learners' ID, name, age, and vocation. Preference includes learners' ID, professional fields, professional degree, and learning expectation. LearnRecord includes learners' ID, time of using the resource, the frequency of using the resource, concerned resources, and the total times of login. SocialInfo is the interactive information of learners including learners' ID, followers, and interest group.

The resource model uses the following triple:

ResourceModel = (BasicInfo, RecordInfo, EvaluationInfo).

BasicInfo includes static information such as number, name, type, subject, and publisher. RecordInfo includes resource number, the number of comments, the number of people who pay attention to resource, and the number of people who have learned the resource. EvaluationInfo includes each learner's rating information for resources. RecordInfo and EvaluationInfo are updated dynamically by system according to the learners' use and feedback.

The two models acquire the data from data collection layer which is in the bottom of the architecture. The data collection layer stores various resource data such as learners' social network data, behavioral data, and learning preference. Data

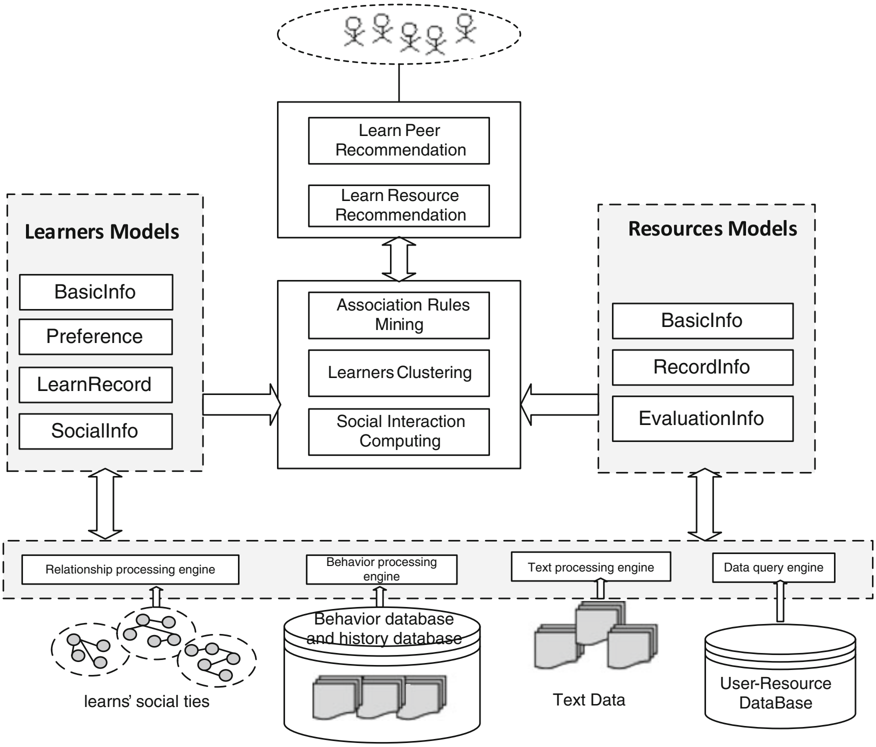

Fig. 16.1 The architecture of the learning recommender system

engine can extract effective information from these data sources to construct learner model and resource model. Interactive calculation calculates learners' interactive information mainly according to different demands of learning peer recommendations. Clustering calculation uses some clustering algorithms to divide learners into different cluster groups, which is based on learners' interest and character. Association rules mainly mine accessing behavior of the learners who are in the same cluster to find the association relationship among the resources.

16.3 Social Interaction Computing for Peer Recommendation

Social relationship analysis focuses on interaction relationship among users in the smart learning environments, such as interaction frequency and friendship. On the basis of our previous studies of online learning community activities [6], user credibility networks are constructed toward the various item topics. It consists of three steps: category-based user networking, credibility value assignment based on social ties, and user feature measurement for credibility refinement.

Category-based user networking is for networking users on different topics. Currently, we infer the circle of users according to their concerning items that can be divided into different categories. Credibility value based on social ties is to assign credibility value between users based on the combination of strong ties and weak ties.

User feature is computed based on four indicators, namely expertise, influence, longevity, and centrality. Expertise is used to measure users' expertise in a specific category. Influence indicates whether a user is influential in a certain category. Longevity indicates an individual's persistence, which can be computed according to user behaviors. Centrality indicates an individual's concentration on a specific topic. By combining user credibility network and user rating matrix, this social recommender system can provide learning peers and domain experts' recommendation.

16.4 Resource Recommendation Method-Based Cluster Analysis and Association Rule Mining

In the learning process, learning resources have some intrinsic orders in similar users' learning processes, for example, students who major in computer science always choose data structure after they study C language course. Therefore, it is important to mine association rules of resource through clustering students who have similar characteristics. In this way, we can improve the resource recommendation.

We combine two data mining algorithms: simple k-means clustering algorithm and Apriori association rule algorithm. Simple k-means algorithm is a type of unsupervised algorithm in which items are moved among the set of clusters until the required set is reached. This algorithm is used to classify the dataset, provided the number of clusters is given in prior. Apriori association rule is used to mine the frequent patterns in database. And there has been considerable research using association rules in data mining [7]. The association rule algorithm is employed mainly to determine the relationships between items or features that occur synchronously in the database. The main purpose of implementing the association rule algorithm is to obtain resource using relationships by analyzing the data and to use these relationships as a reference during the recommender process. The model of the recommendation mechanism is shown in Fig. 16.2.

16.5 Experimental Study

The experiment on real datasets demonstrates the effectiveness and usefulness of the proposed approach. We crawled learner information and their course selection information from the MOOC College (http://mooc.guokr.com) which is the Chinese online MOOC learning community. The dataset contains 2000 learners' information and 12,076 valid course selection records. As for data processing, firstly,

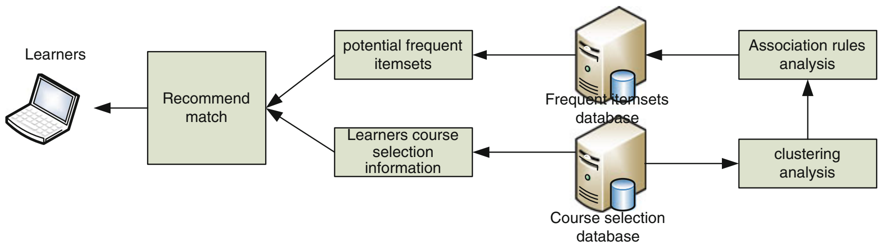

Fig. 16.2 The model of the recommendation mechanism

we use clustering algorithm to cluster. Learners who have the similar interest, knowledge level, and learning expectation are combined into the same group through clustering. Then, we use association rule mining to mine course association relationship among each group. Table 16.1 presents the association results of one group. The main interest of this group's member is computer science, and the knowledge level for the group is intermediate level. This cluster contains 4014 information of courses selected by 372 students and involves about 40 online courses.

Table 16.1 shows course association rules of system mining. System needs to configure mine support and mine confidence. Confidence is a measure of strength of

Table 16.1 The results of course association rule based on Apriori algorithm

No.	Course A	Course B	A → B Conf (%)
1	Getting and cleaning data	R programming	92.8
2	Getting and cleaning data	Data scientist's toolbox	89.2
3	R programming	Data scientist's toolbox	84.6
4	Getting and cleaning data	Exploratory data analysis	67.8
5	Data scientist's toolbox	T and machine learning	62.1
6	Data scientist's toolbox	R programming	58.6
7	Exploratory data analysis	R programming	55.0
8	R programming Data scientist's toolbox	Getting and cleaning data	54.5
9	Algorithms: design and analysis (part 1)	Machine learning	53.1
10	R programming Data scientist's toolbox	Exploratory data analysis	52.5
11	Data scientist's toolbox R programming	Machine learning	52.0
12	Model thinking	R programming	51.6
13	R programming Data scientist's toolbox	Introduction to statistics	51.5
14	Data scientist's toolbox Machine learning	An introduction to interactive program in Python	50.0
15	C language programming	Data structure	50.0

the association rules. In Table 16.1, "A → B Conf" means percentage of course records that contain course A also contain course B together. Support is the percentage of course records that contain course A and course B to the total number of course records. In our study, we configure that the minimum support is 0.1 and minimum confidence is 0.5. As a result, we get the following 15 effective association rules which meet this condition.

From the result of association, it seems that there are high associations among learners' course choices. For example, "R programming → data scientist's toolbox conf" is 58.6 %, which means that 58.6 % of learners who have learned "R programming" also have learned "data scientist's toolbox." In addition, we also know that "C language programming" and "data structure" have strong correlation. Therefore, we can recommend information for students according to the relevant rules. If a learner has learned "C language programming" and "getting and cleaning data," we should recommend "R programming," "data scientist's toolbox," "exploratory data analysis," and "data structure" for him based the association rules.

16.6 Conclusion

In this paper, we propose a general architecture of learning recommender system for smart learning environment. The kernel idea is to adopt data mining approach to recommend learning resources and utilize social interaction computing to recommend learning peers. By combining k-means and Apriori algorithm, the proposed recommender system can recommend suitable resources more easily and effectively. As well, users' credibility network is constructed for recommending learning peers. The experiment on real datasets demonstrates the effectiveness and usefulness of the proposed approach.

The proposed recommender system is still in its early stage, and more work needs to be done in the future, such as (1) providing sequential-based resource recommendation; (2) considering the implicit attributes of learners; and (3) implementing the recommender system prototype and applying it in the practical settings.

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Chapter 17
Investigating Students' Blogging Activity in Project-Based Learning Settings

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Abstract Blogs are increasingly popular Web 2.0 tools in educational settings, being successfully used both for individual and collaborative learning. This study explores the use of blogs as communication and collaboration tools in project-based learning settings. Fifty-three computer science students participated in the study and their learning activity is analyzed from three perspectives: (i) blog posting data recorded by a dedicated learner tracking platform; (ii) content analysis of blog contributions based on Community of Inquiry framework; and (iii) students' perceptions regarding their learning experience, as reported in opinion surveys. Overall findings confirm blogs' affordances for educational settings, and in particular for project-based learning scenarios, fostering collaborative knowledge construction, and boosting student satisfaction.

Keywords Blog · Project-based learning · Social learning environment · Collaborative learning · Community of Inquiry

17.1 Introduction

Blogs have been successfully used in education during the past several years, for various disciplines of study, in different learning settings and with a variety of pedagogical objectives [1–6]. Indeed, according to the literature [1], blogs can be used to support various instructional scenarios, enhance writing skills, and promote critical and analytical thinking as well as creativity and strengthen social interaction. They also provide opportunities for students to learn from each other and to create connected communities among them. Learner-generated content can be shared not only among classmates but also with a wider external community [7].

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Blogs have been found to increase competitiveness, involvement, and motivation and enable learners to express their unique identity. Finally, they provide an opportunity to make invisible knowledge and learning visible, especially in case of informal and life-wide learning [8].

More specifically, blogs could be used to support a large set of learning activities, such as the following:

- to create a portfolio from a collection of student assignments, essays, and reflections (published as posts) and the corresponding instructor feedback (published as comments);
- to maintain a learning diary, for reflecting on the learning experience and for tracking the learning progress (due to the time-ordered sequence of posts);
- to publish ideas and interesting findings related to the course;
- to share blogs of interest by adding them to the blogroll;
- to reflect on the reading material;
- to introduce oneself to peers in distance-learning settings;
- to document the development of the project/learning activity, reporting each accomplished task;
- to describe problems encountered, ask for help, and receive feedback from peers;
- to write constructive comments;
- to communicate and collaborate with peers working on the same project/assignment and regulate group work; and
- from a teacher's point of view: post course announcements and news, publish lecture resources, and provide feedback to students [1, 7, 9].

Blogs have started to be used also to support communication and collaboration in project-based learning settings (PBL), either alone [10, 11] or in combination with other social media tools [12, 13]. This can be explained by the strong socio-constructivist component of PBL, according to which knowledge is constructed by the individual, through collaborative efforts and social interactions [14]. Therefore, relying on a social media-based learning environment for implementing a PBL scenario appears beneficial [15]. However, systematic analyses regarding blog's affordances for this type of instructional scenario are scarce. The present study adds to the literature by offering a detailed experience report on the use of blogs in PBL, in the context of a computer science course. The novelty of our approach consists in the in-depth investigations performed, relying both on objective data (students' contributions on the blog, analyzed both quantitatively and qualitatively) and subjective data (students' perceptions collected by opinion surveys); a more comprehensive perspective can thus be obtained.

The rest of the chapter is structured as follows: the context of our study is described in the next section. Subsequently, Sect. 17.3 reports on the number and distribution of blog entries, while their content is analyzed in Sect. 17.4. Next, students' perceived learning experience with blog support is explored in Sect. 17.5. Finally, some discussions and conclusions are summarized in Sect. 17.6.

17.2 Study Settings

Our study took place during the first semester of the 2014–2015 academic year, at the University of Craiova, Romania. The context is a course on "Web Applications Design" (WAD), taught to 4th year undergraduate students in computer science. A project-based learning approach is used, in which learning is organized around the development of an authentic Web application. Students collaborate in teams of 3–4 peers, in order to build their chosen system (e.g., a virtual bookstore, an online auction Web site, a professional social network, an online travel agency, etc.); each student takes various real-life roles in different stages (e.g., system analyst, database specialist, interface designer, application architect, programmer, tester, and project manager). We have been applying this instructional scenario, with various refinements, for the past 5 years [15, 16].

The PBL scenario is implemented in blended mode, with weekly face-to-face meetings between each team and the instructor, complemented by the use of three social media tools (wiki, blog, and microblogging tool) for online communication and collaboration activities. MediaWiki is intended for collaborative writing tasks among the team members, for gathering and organizing their knowledge and resources, and for clearly documenting the project. Blogger is used for reporting the progress of the project (i.e., a kind of "learning diary"), for publishing ideas and resources, and for providing feedback and solutions to peer problems; each team has its own blog, but inter-team cooperation is encouraged as well. Twitter is meant for staying connected with peers and posting short news, announcements, questions, and status updates regarding the project. These three Web 2.0 tools are integrated in a social learning environment called eMUSE (**e**mpowering **M**ash**U**ps for **S**ocial **E**-learning). The platform provides support for both students and teachers: common access point to the social media tools, basic administrative services, learner tracking and data visualization, and evaluation and grading support. The whole range of functionalities provided by eMUSE can be found in [15].

The student assessment takes into account both the final product delivered at the end of the semester and the continuous collaborative work carried out on the Web 2.0 tools. There are also 4 compulsory intermediary presentations, in order to engage students more and discourage the practice of activity peak at the end of the semester.

The study participants are 53 undergraduate students (20 females and 33 males), split in 14 teams (11 with 4 members and 3 with 3 members), who were enrolled in the WAD course. For the current study, we focus on students' activity on the blog, from 3 research perspectives: (i) the quantitative data collected and recorded by eMUSE; (ii) the qualitative analysis of the blog content; and (iii) the subjective perception of the students regarding their learning experience with blogs. Each of these perspectives is addressed in turn in the following 3 sections.

17.3 Students' Blogging Activity

As explained in the previous section, students' activity was tracked and monitored throughout the semester by means of the eMUSE platform. The system gathers learner actions from each of the social media tools and stores them in a local database for further processing (together with a description and an associated time stamp). Based on these data, the platform provides a range of statistics and graphical visualizations, which support students and instructors in self-monitoring and evaluation, respectively; in this section, we focus on the blogging part of learners' activity. Figure 17.1 includes a screenshot from the eMUSE dashboard at the end of the semester, illustrating the distribution of students' actions on the blogs throughout the weeks (first 2 charts), as well as the proportion of blog posts versus blog comments (third chart).

As can be seen, the periods with the lowest activity level were at the beginning of the semester (Weeks 1 and 2—before the actual introduction of the project tools and tasks) and during the winter holidays (Weeks 13 and 14). The activity peaks coincided with the intermediary presentations (Weeks 5, 7, 9 and 11) as well as the final presentation (Week 16).

A total of 449 student blog contributions were recorded: 405 posts and 44 comments. This amounts to an average of almost 8 posts and 1 comment per student. While this may not seem like a lot, it should be remembered that the blog was just one of the three social media tools employed by the students for their project. The low number of comments can be explained not necessarily by a lack of interaction, but mostly by the perceived purpose of the blog: a place for sharing experience, organizing knowledge, and finding interesting resources, more than a medium for communication or feedback provisioning; the latter roles were mostly fulfilled by Twitter and face-to-face discussions. A more in-depth analysis of the blog contributions and its perceived roles are provided in the next 2 sections, respectively. Another potential explanation for the low number of comments is that sometimes students answered peers in new posts rather than through comments to the original post; occasionally, they even titled their posts accordingly (e.g., "*RE: Sites Color change*").

Finally, it is worth investigating also the distribution of blog contributions per student: A significant variation among students and teams was recorded, as shown in Fig. 17.2. Two of the teams were virtually inactive (with 1 and 3 blog posts, respectively) and their members eventually dropped out of the course. These disparities between students' work with social media tools are in-line with the previous findings [10, 16, 17] (generally due to social loafing and free-rider issues). Involving students more uniformly in blogging and learning activities in general would be beneficial, and we address this issue in more detail in the Discussion section.

Fig. 17.1 Summary charts provided by eMUSE at the end of the semester

17.4 Content Analysis of Blog Contributions

So far we analyzed the blog contributions from a quantitative point of view, based on the data provided by eMUSE; in this section, we introduce also a qualitative analysis, based on the Community of Inquiry framework [18]. The decision to use an existing coding scheme for content analysis rather than develop a new one was

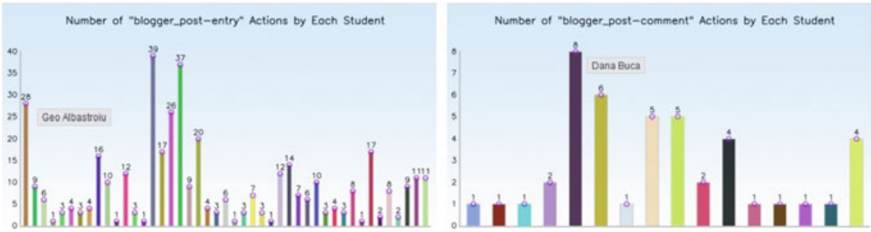

Fig. 17.2 Excerpt from eMUSE dashboard, illustrating the distribution of blog contributions per student: posts in the *left chart* and comments in the *right chart* (students' names appear as tooltips on each bar and only students with at least one contribution are included)

motivated by the proven validity of the instrument [19], as well as its popularity and widespread adoption [20].

The Community of Inquiry (CoI) model was proposed in [18] and has socio-constructivist roots. It identifies three essential and interdependent elements of an educational experience in an online learning community:

- Cognitive presence (the extent to which learners are able to construct meaning through sustained reflection and discourse);
- Social presence (the ability of learners to identify with the community and develop interpersonal relationships by projecting their personal characteristics into the community); and
- Teaching presence (design, facilitation, and direction of cognitive and social processes to support learning).[1]

While CoI framework was initially introduced for computer conferencing, it was subsequently extended to other asynchronous communication spaces between students. Recently, it was applied also to social media tools, such as blog [10], Twitter [21], or SecondLife [22]. Its suitability for blogs comes from the fact that educational blogs integrate both a content space and a discussion space, which are built collaboratively [10].

For our study, we decided to consider each blog entry (post or comment) as a unit of analysis, following the suggestion in [10]. All 449 blog entries were manually coded using the coding scheme (categories and indicators) proposed in [23]. Since only the student blogs were analyzed (not also the teacher blog), only the first 2 presences (cognitive and social) are considered. The resulted classification is included in Table 17.1.

The results confirm the blog affordances to support both social and cognitive presences. The cognitive components (63 %) outweigh the social components (37 %), which is in-line with students' perceived role of the blog in the current learning scenario (primarily a content space and secondarily a discussion space).

[1]Community of Inquiry Model, available at: https://coi.athabascau.ca/coi-model.

Table 17.1 Classification of blog posts and comments according to CoI framework

Element	Category	Indicators (examples according to [23])	Number of posts and comments
Cognitive presence	Triggering event	Recognize problem; sense of puzzlement	4
	Exploration	Exploration within the online community; exploration within a single message; information exchange; suggestions for consideration; leaps to conclusions	245
	Integration	Integration among group members; integration within a single message; connecting ideas and synthesis; creating solutions	32
	Resolution	Vicarious application to real-world testing solutions; defending solutions	3
Total			284
Social presence	Affective	Expressing emotions; use of humor; self-disclosure; use of unconventional expressions to express emotion; expressing value	11
	Open communication	Continuing a thread; quoting from others' messages; referring explicitly to others' messages; asking questions; complimenting, expressing appreciation; expressing agreement; expressing disagreement; personal advice	106
	Group cohesion	Vocatives; addresses or refers to the group using inclusive pronouns; phatics, salutations and greetings; social sharing; course reflection	48
Total			165

More than half of the blog posts belong to the exploration phase of learning, in which students find and share interesting resources (mainly online tutorials), exchange ideas and information, provide explanations, and make suggestions for their team members. The phases of integration and resolution are captured in less than 8 % of the blog posts; this can be explained by the fact that complete solutions are generally lengthy and they are mainly documented on the wiki (the blog records predominantly the progress up to the solution). We can also see that students tend to post when they have some useful resources to share, not when they encounter a problem or puzzlement; hence, the triggering phase of learning is much less documented on the blog. Students are not much inclined to post questions and ask for help, which also explains the low number of comments and feedback messages (as noted in the previous section).

The posts and comments reflecting the social presence accounted mainly for discussions between students, notifications regarding project progress, encouragements, and compliments for peers' activity. Team spirit and group cohesion were also apparent in a significant number of posts. Few off-topic, small-talk posts were recorded, as well as few posts expressing emotions—students preferred to use the blog in a slightly more formal manner.

As a complement to the quantitative and qualitative analysis of students' contributions on the blog, in the next section we investigate students' subjective perceptions on their blogging activity.

17.5 Students' Perceptions on Blogging

At the end of the semester, students were asked to fill in a survey regarding various aspects of their learning experience for the WAD project. Forty-one students (about 77 %) chose to answer the questionnaire and in what follows we summarize their opinions related specifically to the use of blogs.

Most respondents (over 70 %) found it easy or very easy to learn how to use the blog as well as actually use it; the vast majority did not encounter any technical problems while using the blog.

The main roles fulfilled by the blog (ordered based on the importance assigned by the students) are (i) learn how to use the tool (73.17 %); (ii) exchange experience (53.66 %); (iii) help organize knowledge (48.78 %); and (iv) find interesting/useful information (46.34 %). (Please note that since students could select more than one role, percentages add up to more than 100 %.) Other important purposes of the blog, mentioned by at least a third of the students, include the following: (i) improve writing skills; (ii) receive feedback; (iii) improve collaborative skills; and (iv) increase competitiveness. The majority of the students reported using the blog because they considered it to be really useful for the project or because it was interesting/fun. However, more than a third of the students reported using it mainly for getting the corresponding grade.

We also investigated the level of interaction between teams and found out that more than 75 % of the respondents read other teams' blogs. The main reasons for referring to peers' blogs are (i) looking for information (finding interesting and useful resources); (ii) curiosity (seeing other teams' progress, level of involvement, and work style); (iii) searching for solutions to problems encountered; and (iv) comparison (checking out competition, in order to transfer ideas and increase own motivation). Conversely, the most common reason for not reading peers' blogs was the lack of time, some students preferring to focus exclusively on their own team work.

Overall, about 95 % of the students were at least moderately satisfied with the use of the social media tools for the WAD project; over 73 % reported a higher learning satisfaction compared to traditional project settings. Finally, more than 70 % of the students expressed their support for the use of social media tools in education (with only about 7 % being against it) and expressed their desire to use the WAD project approach for other subjects in the future.

17.6 Discussion and Conclusion

The study presented in this chapter revealed a successful integration of blogs as PBL support tools for a Web Applications Design course. The analysis included three dimensions (usage data recorded by eMUSE platform, content analysis based on CoI model, and student self-reported data), which helped create a more comprehensive perspective compared to related studies.

Overall findings in CoI framework confirm blogs' affordances for educational settings, and in particular for project-based learning scenarios. They support both social and cognitive presences, promoting knowledge construction in online learning communities, as suggested also in [10]. This is in-line with the results of the opinion surveys as well; according to them, students found the blogs easy to learn and use, and especially helpful for exchanging experience, organizing knowledge, finding interesting information, and following the progress of other teams. The majority of the students reported their overall satisfaction with the blog-based PBL approach.

Nevertheless, the proposed PBL scenario also has some downsides. First, the amount of time necessary for accomplishing the project was deemed too high by some of the participants. This could be partially explained by the fact that the instructional settings were a premiere for the students, so they needed some time to get accustomed with the tasks as well as the new collaborative environment [16]. Peers' low level of involvement was also a problem in some of the teams. Indeed, we have also noted this disparity between students' blog contributions in Sect. 17.3. A potential solution for involving students more uniformly in the blogging activity would be to provide automatic feedback and encouragements to low-level activity students throughout the semester, by including an additional functionality in eMUSE platform.

A further area for improvement is students' reluctance to post questions or problems encountered, to show their learning process, not just the results (hence the low number of posts from the triggering phase of learning, as noted in Sect. 17.4). Learners should be more encouraged to ask peers for help and share their incomplete ideas or puzzlements; students' fear of exposure can be alleviated by ensuring a positive group climate and creating an atmosphere of trust and confidence, as suggested in [24].

As future work, we plan to perform a more detailed analysis of the blog content, by investigating the evolution of social and cognitive presences over time and over the different stages of the project; team-level and student-level investigation would also provide an interesting perspective. An automatic content analysis could also be envisioned, as the one suggested in [25]. Finally, additional coding schemes could be employed (as the ones reviewed in [26]), in order to provide a more in-depth analysis of students' blog contributions.

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Chapter 18
How Video Usage Styles Affect Student Engagement? Implications for Video-Based Learning Environments

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Abstract There is a growing number and variety of video-based learning environments; however, the adoption and engagement with them are not always very high. This is partly due to the fact that students do not always use videos as expected. Recent studies have investigated students' engagement toward video-based environments; however, the effect of different usage styles such as platforms used, video duration, watching period, and students' experience on engagement is yet to be explored. This study investigates potential influence of video usage styles on student engagement. Data collected from 40 students who enrolled into a video-assisted course suggest that usage styles affect students' engagement to video materials. In particular, the results demonstrate that previous experience, video platform, video duration, and the watching intensity have significant effect on students' engagement. The overall outcomes are expected to promote theoretical development of students' engagement, video environments design principles, and better and more efficient use of videos, with particular focus on video lectures.

Keywords Video lectures · User-centered design · Usage styles · Engagement

18.1 Introduction

During recent years, the usage of videos for information transfer and learning purposes has increased. The number of institutions and business organizations provides their content using videos; for example, many instructors in higher edu-

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cation are implementing video lectures in a variety of ways, such as broadcasting lectures in distance education [1], delivering recordings of in-class lectures with face-to-face meetings for review purposes [2], and delivering lecture recordings before class to conserve class time and flipping the day for hands-on activities [3]. In addition, the number of for-profit organizations who use training or advertising videos is increasing rapidly.

Due to the importance of students' engagement with videos, interaction designers and instructional designers spend considerable amount of time and money on how these videos can be better provided via different platforms with different designs and affordances to the users. Drawing from the user-centered and interaction design theories [4], one of the most important questions is: *How to increase student engagement with the videos?*

As a step toward this goal and given the different video usage styles (e.g., previous experience, video platform, video duration, and the watching intensity), in this study we attempt to understand how usage styles impact student engagement. In particular, this research included questionnaires incorporating factors regarding students' engagement and questions for identifying their usage styles, and basic analytics drawn from the platform. After users employed two different video systems to assist their studies during a full semester, they were asked to complete the questionnaire based on their intensive experience.

18.2 Background and Hypotheses

Student engagement refers to the state of the student being involved, occupied, retained, and intrinsically interested in something [5]. In this study, engagement is based on students' post-behavior; thus, engagement consisted of users' attitudes, and intrinsic interest [5] after the intense video learning experience. Engagement is beyond the concept of acceptance or usefulness with the medium, which are considered as a subset of engagement [6]. Hence, in our study, we use both students' intention to further use (acceptance) and usefulness in order to investigate students' engagement.

Although videos for learning/training have been employed in the industry and education for many years, several factors regarding learners' engagement with and use of videos have changed. For example, learners can interact with the content in various ways, video repositories have advanced (e.g., iTunes, YouTube), and other interactive and smart video-based systems have appeared (MOOCs, Interactive TV).

Today, advanced video repository systems have seen enormous growth (e.g., videolectures.net, Khan Academy). Most of the 2.0 technologies such as wikis, blogs, and other social media have added video affordances. It is notable that sometimes, the same video is posted on two different platforms (e.g., YouTube and an institutional/organizational platform). With the widespread adoption of different video platforms, new research from the design and learning perspective is emerging.

Therefore, we want our research to make a first step in this direction by examining *whether the difference between a commercial and an organizational video platform affects students' engagement*.

The predictors of continued engagement for technologies would not be the same for all students; this is particularly clear in students with different experiences. For example, the level of Web site browsing experience influences the engagement with it [7]. Most of the times, experienced students react differently from novices; hence, it is natural to expect that *students' experience with videos is a significant factor of their engagement*.

Numerous comments have been made in the past regarding watching intensity. Dale and Pymm [8] have indicated the importance of rewinding, skipping, and other similar affordances to navigate video content. Although research has mentioned several different watching intensity types and navigation, the differences between the two main watching intensity types, users who watch the full video and those who watch only part of it, are yet to be explored. Hence, in our research, we want to examine *whether the watching intensity affects users' engagement*.

Another important video usage style is the preferred video's duration, since some students prefer watching long and detailed videos while others prefer watching short summary video. Although the duration of the videos is fundamental to the design of the video, its effect on engagement is yet to be explored. Video duration is of high importance, since organizations such as TEDx and Khan Academy provide short videos and summaries while other organizations and universities provide longer and detailed videos, mostly of the same duration as traditional lectures—without having any tangible fact behind this choice. Therefore, we want to examine *whether video duration affects users' engagement.*

18.3 Methodology

Sampling The methodology comprised a questionnaire conducted at the end of a full semester video experience. The responses were captured from June to July 2013, and it was clear that participation was voluntary. Forty students who had used how-to and lecture videos from two different video platforms responded, based on their longitudinal experience. Of the respondents, 87.5 % were males and 12.5 % were females, and all were aged between 20 and 23 years (M = 21.7, SD = 1.12), with the exception of one 25 years old. The sample consisted of university students with experience using video lectures on their syllabus (only two had no experience of video lectures). In the clarification letter accompanying the survey, after describing the purpose of our study, respondents were asked to answer the questions based on their video experience. Respondents watched an average of 4.03 videos (out of 12), with the median value being 4 video lectures and a standard deviation of 3.45. In addition, four users (10 %) did not watch a complete video, four watched only one video (10 %), and three (7.5 %) watched all 12 videos.

Measures The questionnaire consisted of two parts: (1) questions concerning the demographics of the sample and the video usage styles (e.g., age, gender, platforms used, preferred duration) and (2) measures of engagement (videos' usefulness and intention to use of videos). We used a 7-point Likert scale anchored from 1, 'completely disagree,' to 7, 'completely agree.'

Statistical Analysis We first carried out an analysis of composite reliability of each construct and dimensionality to check the validity of the scale used in the survey. To do this, Cronbach's alpha indicator was applied and we applied inter-item correlation statistics for the items of the construct. The results of the tests revealed acceptable indices (>0.7). Following this, we evaluated the reliability of the measure. The reliability of an item was assessed by measuring its factor loading onto the underlying construct. In particular, factorial analysis with principal components and varimax rotation for the items of each variable was applied. The factor analysis identified two distinct factors (with three items/question each): (1) usefulness and (2) intention to use. The last step was to test the average variance explained (AVE); the AVE was found to be adequate because it exceeds 0.50.

We then investigated any potential relationships between the usage styles and users' engagement (USE and IU) to the videos. To explore the effect of different usage styles on USE and IU, we used independent sample t-test as this method allowed us to extract reliable results in a normally distributed, homogenous, and particularly small population.

18.4 Research Findings

Analyzing the experience of the respondents, all of them had used videos to attain knowledge (e.g., cooking and how-to videos from YouTube) in the past six months. During the last six months, the respondents expressed that they had watched 31.48 videos as an average value with S.D. of 41.50.

Another noteworthy finding is that seventy percent of the users mentioned that videos should have been connected to a Facebook group. In addition, 17.5 % claimed that using Twitter to distribute and advertise videos would be helpful. Users also endorsed Google Plus+ (10 %), LinkedIn (10 %), etc. Hence, *the need for incorporating social media affordances in video learning platform is clear*.

Regarding the duration of the videos, students' responses varied from 15 to 100 min, with an average value at 37.41 min and S.D. at 20.01. Students' selection of video platforms was varied; the number of viewings on commercial platform (YouTube) was nearly equal to the number of viewings on the institutional organizational video platform, with a significant number of respondents using both platforms. Figure 18.1 shows students' video platform selection.

To investigate students' watching intensity, we asked them to describe how they were watching the videos. Over half of the users (60 %) were watching the full video lecture, while the remainders (40 %) were watching specific parts of the video. Figure 18.1, right, summarizes the results of the watching behavior in our study.

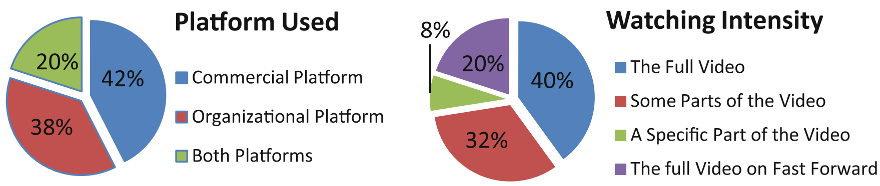

Fig. 18.1 Distribution of the platforms used from students (*left*) and the watching intensity (*right*)

Table 18.1 Testing the effect of usage styles on users' engagement (through USE and IU)

		Mean (S.D.)		T.	Sig.
Video platform		Commercial	Institutional		
	USE	3.77 (1.31)	4.92 (1.29)	**2.31**	**0.029***
	IU	5.16 (1.42)	5.77 (1.05)	1.25	0.221
Experience		Up to 3 videos	More than 3 videos		
	USE	3.72 (1.64)	4.97 (0.99)	**2.95**	**0.005***
	IU	5.19 (1.56)	5.73 (1.12)	1.27	0.213
Watching intensity		The full video	Parts of the video		
	USE	4.65 (1.06)	4.04 (1.69)	1.29	0.207
	IU	5.85 (1.18)	4.94 (1.43)	**2.11**	**0.041***
Video duration		Up to 25 min	More than 25 min		
	USE	3.94 (1.72)	4.71 (1.21)	1.64	0.110
	IU	4.39 (1.29)	5.92 (1.03)	**4.14**	**0.00****

**$p < 0.01$; *$p < 0.05$

To examine any potential effect of (a) video platform type, (b) experience, (c) watching intensity, and (d) video duration, on students' engagement, t-tests were conducted using the four independent variables (a–d) and users' engagement (through USE and IU) as dependent.

The results exhibited in Table 18.1 demonstrate a significant effect of platform used on USE, and a nonsignificant effect on IU; a significant effect of experience on USE, and a nonsignificant effect on IU; a nonsignificant effect of watching intensity on USE, and a significant effect on their IU; and a nonsignificant effect of video duration on USE, and a significant effect on IU.

18.5 Discussion and Conclusions

In this research, we investigated the relationship between students' engagement (through USE and IU) with their video usage styles. This research revealed that there are usage styles related to students' engagement.

The study has implications for theory and practice. The findings demonstrate that users with relatively high experience in videos find them to be more useful. Therefore, it is vital to increase novices' experience; to do so, video platform developers and designers should focus *on incorporating social media and other affordances in order to attract more non-experienced users*.

Video-based environment design and development should strive to increase students' intrinsic motivations and make users feel familiar. For example, the interface and functionalities of the environment should be user-friendly by incorporating standard user-centric design principles. Hence, usability testing and intuitive design on these environments are crucial.

Another important fact that video producers and interaction designers should consider is that many times, short videos are not used consistently, resulting in lower adoption. Hence, although short videos have many uses, student engagement is many times low. Videos are ideal for reviewing and scanning through content; however, motivating users to watch the full videos increases their IU and as a consequence exhibits high engagement. Another important aspect is the possession and maintenance of institutional video environments, or at least to embed videos in an institutional Web site. This is of great importance for students, since we found that they perceive videos provided by an institutional Web site or video-based environment more useful, even when the videos are exactly the same.

Future research would valuably contribute to the understanding of students' engagement with videos. In addition, it would be interesting to see how other usage styles, such as navigation and video genres, are related to student engagement. In the next step of this ongoing project, we will deliver another video-assisted course via a video environment with detailed analytics functionality. Doing so will allow us to discover important design principles for video-environments and the development of video content; hence, we will be able to identify design and practical aspects for improving students' engagement with video learning materials.

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Chapter 19
Student Engagement Pattern in Wiki- and Moodle-Based Learning Environments—A Case Study on Romania

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Abstract The current study draws on the use of Web 2.0 tools to teach advanced computer skills in a Romanian blended undergraduate economics course program. A meta-attribute structure is created using questionnaires and data generated by Web 2.0 tools. The main objective is to provide information on students' engagement behavior on a Moodle platform. Several patterns are obtained by means of applying classification algorithm characteristic to the studied context. The receiver operating characteristic (ROC) regression analysis is used to validate the result, outlining the profile of an actively engaged student. Next, a comparison is made with a similar analysis performed earlier by authors on data gathered from a language course delivered on a wiki platform. The implications of the study are that Web 2.0 tools benefit the learning process on condition that social learning design is incorporated and more emphasis is put on the pedagogical aspects; moreover, teachers may distribute students into groups and focus on those who require more attention to develop the necessary attributes in such an environment.

Keywords Web 2.0 tool · Student engagement · Social learning · Learning analytics

19.1 Introduction

Recent studies on the development of e-learning in Romania have highlighted the various solutions being used for creating virtual learning environments [1, 2], but pedagogical aspects related to their use are yet under-researched. On the other hand, the development of Web 2.0 and social media has given a boost to

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technology-enhanced learning initiatives. Our interest in finding best methods for teaching draws on one of the authors' 12-year experience as higher education teacher of computer science applied in economics and participation in the recent implementation of a Moodle learning management system and both authors pioneering the building and researching of a wiki-based learning environment for teaching foreign languages for specific purposes, with particular attention to various aspects of student engagement behavior. Our findings show that Romanian students' engagement behavior is highly irregular; namely, they become involved only when constrained in different ways [3, 4]. The current study investigates the main processes leading to engagement within Moodle and the wiki platform and aims to find out whether engagement patterns in two disciplines complementary to the core curriculum and known to be essential for professional development are similar, and if so, how they can be used to enhance teacher and learner performance. The article is divided into the following sections: a presentation of research methods and data, findings of a statistical analysis applied to the two learning environments for determining the students' engagement profile, conclusions, and future research directions.

19.2 Research Method

19.2.1 Research Objective and Method

In the literature on TEL, Moodle is known as a tool for quantitative measuring of the social learning process [5] which is studied along two directions: *feedback and engagement* [6] and *feedback and assessment* [7, 8]. In our study, Moodle is used in accordance with the second direction. Our approach is based on the basic assumption that, both Moodle and wikis are software whose pedagogy relies on constructivist and social pedagogy [9]. Yet, we contend that a wiki-based learning environment is more appropriate for teaching with collaborative project and inquiry-based activities. The added value is the subsequent development of cross-curricular academic and professional skills [10, 11].

To verify the above, our research aims to generate a behavior pattern of students studying in a blended learning format consisting of face-to-face weekly meetings and activities performed by one group on Moodle and by the other on a wiki-based platform. As an unsupervised learning technique [12], cluster analysis is commonly used to determine groups within the studied data. In the present study, we applied it for the purpose of defining students' grouping according to their behavior on Moodle and wiki. In the articles [13–15], data mining techniques are used to extract data for teachers to adapt e-learning systems to their students' learning needs and styles, whereas in [20], authors rely on Web mining techniques to organize an e-learning system in accordance with students' recommendations. We employed receiver operating characteristic (ROC) classifier to calculate classification performance metrics performed with SPSS TwoStep algorithm. Comparable approaches were identified in specialist literature, but they were designed and adapted to other sets of data [16–18]. In order to reach our purpose, we set on to determine the number of clusters and the ensuing pattern of student engagement. ROC regression analysis was then used to test the validation of the developed classification model. The analysis model aims to outline the profile of an actively engaged student and help identify errors such as false-positive or false-negative diagnosis/classification.

19.2.2 Research Data

The first study was conducted on a group of 62 students engaged in a blended course of theories of databases for economists, with an online component based on the Moodle platform. Data were collected for a 14-week period corresponding to the first semester of the academic year. During this period, students participated in two types of face-to-face meetings: lectures and hands-on laboratory sessions. The teaching/learning activities were extended on Moodle to provide quick access to course materials and continuous support from the teacher. As this was the first time Moodle was used, the design was rather "traditional" (transmission mode). The attributes were collected by means of a questionnaire: students' *computer driving knowledge* (all of them attended a mandatory first-year course)—1—average and 2—advanced; their *engagement with the Moodle-based materials* measured by monthly number of views/student (Moodle logs); *gender*; *interest* in the study of computer science measured on a 3 level Likert scale; *learning outcomes* for practical activities: grades measured on a 10 level Likert scale. In this context, we considered as acceptable the behavior of a student with at least a view per week during the laboratory activities (4 views in all). An average of 4 grades on the practical activities was calculated for the chapters studied during face-to-face meetings. *The second study* is part of an ongoing research on wiki learner profiles and analyzed students' behavior in a blended language learning course with face-to-face weekly meetings and course management/online activities performed on a wiki platform whose design included also capabilities for independent/collaborative work. Data on 76 participants were collected by a questionnaire and wiki logs. Students' profiles were built up by studying the relations among the attributes: *class participation* and attendance (max: 2), personal wiki pages edits (max: 2); *student-wiki interaction*, measured by the number of views for all wiki pages (including the personal pages), and *independent work*, measured by the number of edits on personal pages.

19.3 Determining Student Engagement Pattern—Findings of Statistical Analysis

The steps of the statistical analysis were similar for both studies. Descriptive analysis reveals that the vast majority of participants were *female* (over 75 %). The *interest* for the study of the disciplines was distributed as follows: database theory—three groups: around half showed a lack of interest, about one-third had an average interest, and less than a third showed a high interest, and English—five groups with: majority high, relative and average interest (about 90 % in all), and low and no interest (below 9 %). *Previous knowledge* was measured for Moodle students by computer driving knowledge, with more than half (55.6 %) having medium and the remaining percentage having medium to high levels; in the case of wiki students, their experience was measured by length of study, with almost 90 % having studied between 5 and 11+ years, and the rest 1 to 4 years). Then, the profile of a student with constant engagement behavior was decided, namely a student with medium knowledge of and highly interested in the discipline, who accesses the learning platform at least 4 times a month and achieves maximum grade at final examination. For this purpose, we chose average values for the studied attributes.

Then, we used SPSS TwoStep classification method to determine the number of specific groups/clusters of students within the data set. Firstly, in the aggregation phase, results show that there are differences between students' participation behavior on Moodle and wiki, with them being grouped in two, respectively three clusters, based on the given set of attributes. The clusters are characterized by the fact that the interclass inertia value significantly exceeds the intraclass inertia values.

In the case of Moodle, cluster 1 (53.2 %) includes individuals with mediocre to low grades for practical activities, low interest for computer science (mostly students with lack of interest and only a few with average interest), and minimal knowledge of computer usage. The amount of views and edits is below the minimum acceptable level allowing buildup of knowledge and skills for minimal course mastery. Cluster 2 (46.8 %) contains individuals with good to very good grades for practical activities; average to high interest for computer science (mostly average interest); and average to advanced knowledge of computer usage. Views and edits are above the minimum acceptable level allowing for good course mastery. Grades indicate that these students definitely acquired the information delivered via the two teaching channels (face to face and virtual). Gender (mostly females) and the level of knowledge previously acquired during the computer driving course represent attributes with characteristic roles, while the rest of the attributes have a discriminatory role. *In the case of wiki*, cluster 1 includes students with a high interest in learning English, 11+ years of study, maximum attendance value, WikiPage graded with average and excellent values, and average to high learning outcomes. Views and edits range between average and low. Cluster 2 includes students with an average interest in learning English, 5–8 years of study, average attendance value, WikiPage graded with average to poor values, and average to poor learning outcomes. The views and edits range between average and high. Finally, cluster 3 includes students with a low interest in studying English, 9–10 years of study, average attendance value, WikiPage graded with average to poor values, and average to poor learning outcomes. The views and edits range from average to low. All in all, around 65 % of the students engage irregularly.

The research continued with the application of ROC curve as a metric to evaluate and compare the performance of the classification model related to students' engagement. The steps were as follows: using a hierarchical logistic regression, followed by a discriminant analysis, and by determining the specific ROC curve classifier. Within the regression, we measured the presence of a relationship between the dependent variable and the combination of independent variables (entered after the control variables) based on the statistically significant result of the chi-square block.

The chi-squared test block probability values were less than or equal to the 0.05 significance level. The null hypothesis (there is no difference between the model with a single constant and control variables versus the independent predictor variables) was rejected. To test the contribution of the relationship between independent predictor variables and dependent variable in the given model, we employed the hierarchical logistic regression model. Next, we tested the hypothesis: There are certain differences in the results of measured attributes of students belonging to the first groups with a low/minimal involvement behavior and the other students with a constant involvement behavior. The hypothesis was confirmed by the Wilk's lambda results. Next, we verified whether the studied attributes were indeed predictive for the model detecting the types of involvement behavior in ongoing course activities (both face to face and virtual). In the case of Moodle, the area under the curve is 0.902, $p = 0.001$, 95 % CI (0814; 1). The studied model represents a discriminant model for 92 % of cases. In the case of wiki, the area under the curve is 0.897, $p = 0.001$, 95 % CI (0.802; 1). The studied model represents a discriminant model for 89 % of cases.

19.4 Conclusions

Finding viable solutions to improve learning experience, performance, and engagement is a priority on the international educational agenda. To date, our research shows that students' engagement is activated only when being persuaded by specific assignments, under teachers' direct supervision or by other means, confirming other findings showing that participants' involvement in the learning process with social media increases only in the presence of certain constraints [19, 20] which, in their view, could be considered as motivational triggers. Even if in our study students were under a certain degree of constraint (e.g., grading), the ensuing pattern of constant engagement is still encountered at fewer students as compared to those presenting irregular behavior. As findings suggest that constant behavior consistently generates good grades while, in the case of irregular behavior, grades seem to reflect earlier knowledge and students' short-term learning abilities, a practical implication is that students' profiles would allow teachers to distribute students according to their learning needs and encourage active and constant involvement by personalized solutions. The limitations of our study are mostly derived from the fact that the engagement pattern was determined on different sets of participants. Another conclusion is that the social learning design embedded in a wiki system could be a better choice in the teaching–learning processes, since it offers an environment for active and social learning. Wikis also allows easy measurement of student participation across several dimensions such as the degree of individual engagement and the ability to collaborate with other colleagues. A possible alternative is for the author to redesign the Moodle course by incorporating wikis and blogs, with more activities that involve social and active learning. In addition, we deem it necessary to analyze the social and cultural environments responsible for the students' and teachers' engagement as well as the society's response to new challenges and innovation.

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Chapter 20
Integrating Motivational Techniques into Learning Management Systems

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Abstract Motivation is a key factor in education. However, learning systems typically do not directly consider motivational aspects to increase students' motivation. While there are a few systems that tapped into this area, they use either one motivational technique that can be applied in different settings or multiple motivational techniques that are then bound to a specific setting (e.g. a specific course/topic). In this paper, we propose the design, implementation and verification of four motivational techniques as well as a tracking mechanism to gather information on how students use the respective techniques. These techniques are system independent and content independent, and can therefore be used in any learning system and for any course. The motivational techniques were integrated into Moodle and verified through case studies. By integrating motivational techniques into learning systems, students can benefit from increased motivation, which again can have a positive impact on their overall performance.

Keywords Motivation · Motivational techniques · Learning management systems

20.1 Introduction

Motivation is a very important factor in education as it is the reason why learners engage in certain behaviour [1, 2]. A lot of research has been done on motivation in education, and several theories and models have been proposed that suggest how

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learners can be motivated and accordingly how courses should be designed and taught in order to motivate learners. Most of these guidelines focus on the preparation of learning materials, the presentation of topics and the teaching style used in lectures, mainly in face-to-face settings. While these are all important ways of increasing students' motivation, with the growing popularity of online learning, an additional opportunity arises for increasing students' motivation. Online systems such as learning management systems such as Moodle [3], Blackboard [4] and Sakai [5] are more and more used, either in completely online settings or in blended settings where students have face-to-face classes and use online learning. While these systems currently do not directly consider motivational aspects, they have the capacity to provide students with motivational techniques in order to increase their motivation and therefore their learning.

In our previous work [6], we identified eleven motivational techniques that were considered as most suitable to integrate into learning systems. These techniques have been selected based on a comprehensive literature review and with respect to their capabilities to motivate learners. Each technique is based on sound motivational theories and models, and most of them have been successfully implemented in prototype systems to show their impact on motivation. In this set of techniques, we only considered techniques that are domain independent and content independent, which makes it possible to use these techniques in any learning system and course, without the need to rewrite or extend the content of a course.

In this paper, we propose the design, implementation and verification of four of these motivational techniques, together with a tracking mechanism that allows gathering data about how motivational techniques are used. The motivational techniques have been designed in a system-independent way and were then implemented as a block for the learning management system Moodle. The proposed motivational techniques can benefit learners by providing them visualizations about their progress in the course and their pace compared to other learners, empowering learners to see their exact position in the course in terms of their progress, providing them with rankings to see how they perform in comparison with other learners and acknowledging achievements with awards to recognize hard work and engagement in the course.

The remainder of the paper is structured as follows. The next section discusses background on motivation in education and related works. Section 20.3 introduces the four motivational techniques and the tracking mechanism. Section 20.4 presents case studies to demonstrate how the motivational techniques work. Section 20.5 concludes the paper.

20.2 Background and Related Work

Motivation is based on different factors such as personal beliefs, feelings and/or preferences, and influences every behaviour someone engages in. In the context of education, motivation is important for learning as it can direct students' behaviour towards achieving a certain goal, increase a student's willingness to put more effort towards achieving a goal, increase student's energy and persistence towards achieving a goal and as a consequence, lead to improved student performance where students achieve their learning goals [7].

Several motivational theories and models exist, aiming at explaining why people/learners are motivated and how to increase their motivation. One of the main motivational models in education is Keller's ARCS model [8], which is used to design motivational strategies into instructional materials to improve the motivational appeal. The ARCS model consists of four conceptual categories (attention, relevance, confidence and satisfaction) which are conditions that need to be met for people to become and remain motivated. The attention category includes perceptual and inquiry arousal. The relevance category includes goal orientation, motive matching and familiarity. The confidence category includes learning requirements, success opportunities and personal control. The satisfaction category includes intrinsic reinforcement, extrinsic rewards and equity.

From such motivational theories and models, motivational techniques can be derived which are practical tools and mechanisms of increasing motivation. Such motivational techniques can be integrated into learning systems to increase motivation of learners. There exist a few prototype systems that investigated the use of motivational techniques. For example, Huett et al. [9] found in an experiment that ARCS-based e-mail communications can lead to an increase in motivation, higher retention rate and a lower failure rate than the control group who did not receive such e-mails. Code et al. [10] developed a goal setting kit (GSK) that allows students to set and manage their goals in an e-learning course. Comtella [11] is a file and bookmark sharing system that includes motivational techniques such as hierarchical memberships, rewards, top users, best papers of week list, personalized messages and ratings, as well as rewards active users with better quality of service. Another system that uses motivational techniques is iHelp. iHelp [12] is an intelligent helpdesk system used in courses, where helpees pay and the helpers earn system credits redeemable for prizes at the end of the term. The system includes motivational techniques such as emoticons, a top helper list and an animated avatar.

While the examples above show that motivational techniques are already used to help online learners to increase their motivation, it can also be seen that these systems are either using multiple motivational technique but are then very domain dependent or use only one technique in a generic setting. Our research is different as we propose the use of multiple motivational techniques in a generic setting, so that learners can benefit from multiple techniques and these techniques can be used in different learning systems and courses.

20.3 Proposed Motivational Techniques

This section introduces four motivational techniques: progress timeline, progress annotation, ranking and awards, together with a tracking mechanism that allows gathering data from learners about how they use the respective motivational techniques. In our previous work [6], these motivational techniques have been identified as particularly useful as they are domain independent and content independent and, therefore, can be integrated into any learning system and any course. The techniques have been designed in a generic way and were then implemented as a block for the learning management system Moodle. This *Motivational Techniques* block is visible on each Moodle page and provides overview information for each of the four motivational techniques, with options to navigate to the main interfaces of the respective motivational technique and to customize the motivational technique. In the following subsections, each technique is described in more detail.

20.3.1 Progress Timeline

The *progress timeline* technique helps learners in (1) monitoring their progress through a course based on milestones—a predefined collection of assignments, quizzes, exams or any other graded components of the course and (2) showing them their progress in relation to the average progress of the class in an anonymous format. This technique builds on the confidence and satisfaction categories of Keller's ARCS model [8]. Through this technique, learners are provided with a tool which enables them to visualize the timeline of successfully completed as well as upcoming milestones. This in turn assists learners with their personal time management and strengthens their belief that they can master the learning tasks. Furthermore, the information on how a learner has progressed through the course in relation to his/her classmates can motivate him/her to work at the same or quicker pace.

Figure 20.1 depicts the interface of the *progress timeline* technique, integrated into Moodle. The predefined milestones are plotted on the *x*-axis, and time (in weeks) is shown along the *y*-axis. The chart consists of three lines: (1) the green line represents the ideal/recommended timeline, which is the timeline of the milestones as suggested or requested by the instructor (considering that while some online courses have strict deadlines, many courses allow students to submit such milestones at their own pace); (2) the black line represents the learner's timeline in terms of his/her own progress in the course; and (3) the grey line represents the average timeline in terms of the average progress of all students enroled in the course.

When setting up the *progress timeline* technique for a course, the teacher can select which learning objects should be considered as milestones and what the ideal day/week of completion would be for each milestone.

20.3.2 Progress Annotation

While the *progress timeline* technique mainly deals with providing information to the learner regarding the time in which graded course components should be ideally

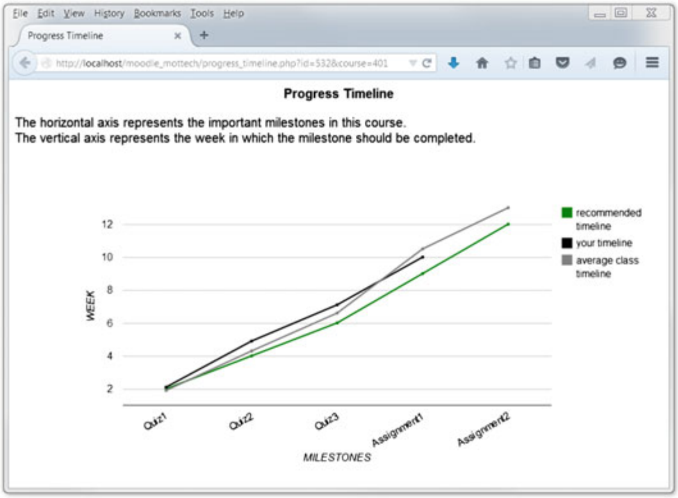

Fig. 20.1 Interface of the *progress timeline* technique

completed and helps in maintaining a good pace, the *progress annotation* technique helps the learner keep track of the status of the various learning objects in the course by tagging learning objects as completed, in progress or not started. This technique builds on the confidence and satisfaction categories of Keller's ARCS model [8]. It empowers learners by displaying their exact position in the course with respect to completed learning objects and can assist them with their time management.

The implementation of the *progress annotation* technique consists of two parts. First, the learners can tag each learning object in the course as completed (by clicking on the checkmark symbol), in progress (by clicking on the diamond symbol) or not started (which is selected by default but can be reselected by clicking on the X symbol). Second, the learners can access an overview page via a button in the *Motivational Techniques* Moodle block showing their progress distribution for the course. Figure 20.2 illustrates the functionality to tag learning objects, and Fig. 20.3 shows the overview chart based on the learner's selection of tags for learning objects.

When setting up the *progress annotation* technique for a course, the learning objects are automatically detected by the system during installation.

20.3.3 Ranking

The *ranking* technique is used to sort learners based on certain criteria. Learners can be ranked, for example, on their performance, the amount of time they spend online and milestones reached in the course. The *ranking* technique is used in other

Fig. 20.2 Progress annotations in a course

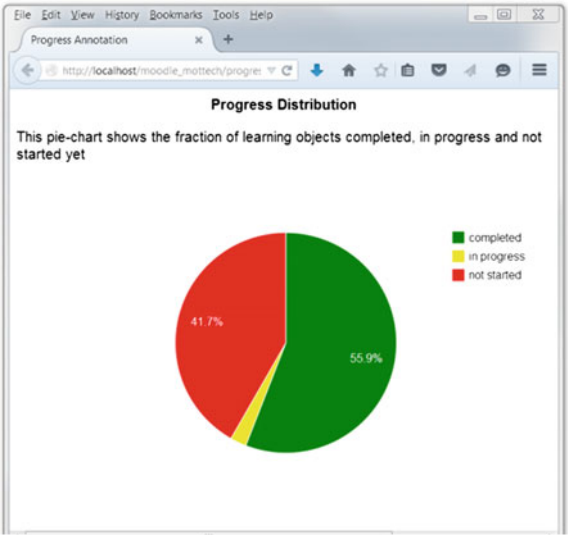

Fig. 20.3 Progress distribution

systems such as Comtella [13] which ranks learners based on the quality and quantity of their contributions and iHelp [12] which displays a top helper list. With the *ranking* technique, a learner is rewarded or satisfied by statistics that are displayed and allow the learner to compare themselves with other learners, which builds on the satisfaction category of Keller's ARCS model [8]. Learners can use the displayed information to try to continually improve.

For each learner, the top five rankings are displayed in the *Motivational Techniques* Moodle block with a link to the main menu for all rankings and a link for the student options. A cron process runs in the background to generate the

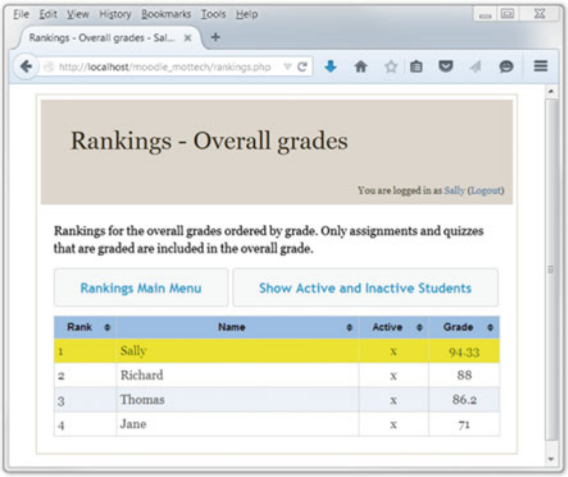

Fig. 20.4 Overall grades

rankings at a scheduled time. Fourteen different rankings have been implemented, together with an overview page that shows all ranks of a learner. These fourteen rankings show grades of assignments, grades of quizzes, overall grades, total number of awards achieved, overall time online, time online in current month, overall number of posts submitted, number of posts submitted in current month, overall post ratings, post ratings in current month, overall reading of all posts, reading of all posts in current month, amount of time it took to reach each milestone and pace to complete milestones.

Figure 20.4 shows a screenshot of a ranking page. The information displayed for each ranking is the rank achieved, the learner's name and the value being ranked on (e.g. grade and time spent). Learners can select to see active and inactive learners or only active learners to compare their results with. In rankings where data are collected over multiple months, learners can see the overall result and results for each month. The current learner is highlighted in yellow in the rankings. Furthermore, learners are able to customize whether they want their names shown or be anonymous.

When setting up the *ranking* technique for a course, available ranking categories are automatically detected by the system.

20.3.4 Awards

Learners are provided with an incentive and/or recognition with the *awards* technique. A learner can either achieve or not achieve an award, and awards can be based on a scale or levels. The *awards* technique is used in other systems such as Comtella [13] which awards active users with better quality of service and iHelp [12] where postings with the highest scores are awarded higher visibility. The *awards* technique rewards a learner and therefore builds on the satisfaction category of Keller's ARCS model [8]. Learners can be motivated through this technique since they are provided recognition and a sense of accomplishment.

The top five awards are displayed in the *Motivational Techniques* Moodle block with a link to the main menu for the awards and a link for student options. A cron process runs in the background to generate the awards at a scheduled time. Twelve different award categories have been implemented, together with an overview page showing all achieved awards. These twelve categories provide awards related to grades of assignments, grades of quizzes, overall grades, completed course milestones within a time period, overall time online, time online in current month, overall number of posts submitted, number of posts submitted in current month, overall post ratings, post ratings in current month, overall reading of all posts and reading of all posts in current month. While these are similar categories as used for rankings, the two techniques aim at motivating learners in different ways. In the *ranking* technique, learners are shown a particular rank in relation to their classmates, allowing them to compare themselves to their classmates. The *awards* technique is solely depending on the individual learner's achievements in a course, independent of the achievements of their classmates. Accordingly, learners are motivated to reach certain thresholds (e.g. completing a course milestone within a certain period of time and achieving a certain grade) in order to get a bronze, silver or gold award.

Figure 20.5 shows the interface of one of the awards categories. The information displayed for each award category includes the learners' names and the awards achieved ordered by highest to lowest award achieved. Learners can select to see active and inactive learners or only active learners to compare their results with. For

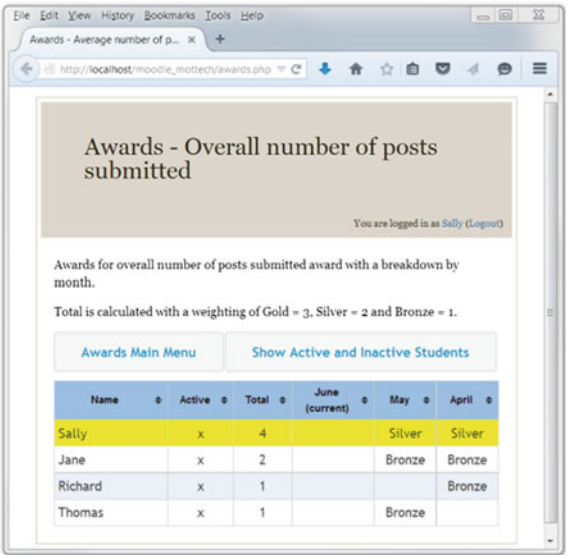

Fig. 20.5 Overall number of posts submitted

awards where data are collected over multiple months, learners can see their awards in each month and a total weighted score summing up their awards for each month. The current learner is highlighted in yellow in the awards interfaces. Furthermore, learners are able to customize whether they want their names shown or be anonymous.

When setting up the *awards* technique, available awards categories are automatically detected by the system and teachers can customize parameters for the awards such as thresholds for awards and their weights.

20.3.5 Tracking Functionality for Motivational Techniques

In order to understand how students are actually using the different motivational techniques, tracking functionality has been designed and implemented that logs learners' behaviour and actions related to the motivational techniques, including which techniques and pages the learner visited and how long he/she visited these pages. Such information provides valuable insights into how often the techniques are used by different learners in different situations and, in combination with other data, can help to determine whether learners actually benefit from these motivational techniques.

To implement such tracking mechanism, each time a learner is using the motivational techniques (e.g. by visiting a ranking page and tagging a learning object), and a log entry is created in the Moodle database. This log entry consists of the following information: a timestamp, the learner's id, the course id and the visited page together with information on the motivational technique.

20.4 Case Studies Demonstrating the Motivational Techniques

In this section, we present a case study for each motivational technique to verify and illustrate how each motivational technique works.

To illustrate the *progress timeline* technique, let us consider a learner named Diana who is very close to the end of a course. Diana has already completed most of the milestones of the course, namely three quizzes and one assignment, and only has one assignment left to complete. While Diana can go through the course in her own pace, the instructor recommends completing Quiz 1 by the end of week 2, Quiz 2 by the end of week 4, Quiz 3 by the end of week 6, Assignment 1 by the end of week 9 and Assignment 2 by the end of week 12. Let us assume in this example that most students follow the respective recommendations, but there are some delays. Accordingly, on average, Quiz 1 is completed even shortly before week 2, Quiz 2 is completed after 4 weeks and 2 days, Quiz 3 is completed after 6 weeks and 4 days, Assignment 1 is completed after 10 weeks and 3 days, and Assignment 2 is completed after 13 weeks. Let us also assume that Diana had a little delay for Quiz 1 and submitted it after 2 weeks and 1 day, Quiz 2 was submitted after 4 weeks and 6 days, Quiz 3 was submitted after 7 weeks and 1 day, Assignment 1 was submitted after 10 weeks, and Diana has not submitted Assignment 2 yet. Based on these assumptions, Diana would see the chart presented in Fig. 20.1. The chart shows that Diana took more time than recommended by the instructor for all so far submitted milestones, and while for Quiz 1, Quiz 2 and Quiz 3, she took more time than the average, and Diana did make up some time when submitting Assignment 1, which was submitted earlier than average.

To illustrate the *progress annotation* technique, let us consider another learner named Jon. Jon has used the *progress annotation* technique and tagged the learning objects that he has completed or is currently working on. Figure 20.2 shows a snapshot of the learning objects that he tagged. Overall, there are 127 learning objects in the course. Jon already completed 71 learning objects, and he is currently working on 3 learning objects in parallel, which include an assignment, a content page and a forum where he posted a question. The other 53 learning objects are not started yet. When Jon clicks on the 'View Progress Distribution' button in the *Motivational Techniques* Moodle block, he can see the diagram depicted in Fig. 20.3, showing his current progress distribution. In this diagram, it can be seen that Jon completed already 55.9 % of the learning objects, he is working on 2.4 % of the learning objects, and there are still 41.7 % of learning objects to complete.

To illustrate the *rankings* technique, let us consider another case. Let us assume a course where by April 1st, four students (Jane, Richard, Sally and Thomas) started. After two months, each student has completed some of the graded course components in the course (e.g. quizzes and assignments). Table 20.1 shows the grades achieved by the four students on completed gradable course components in the first two months. Based on these grades, the weighted average grade of all completed gradable course components is calculated. When Sally takes a look at the ranking for overall grades, she would see the interface depicted in Fig. 20.4.

To illustrate the *awards* technique, we look at the awards for the overall number of posts submitted and assume that Jane, Richard, Sally and Thomas are now in the

Table 20.1 Example of students' grades on gradable course components

Submission date	Gradable course component	Student	Weight	Grade (0–100)
20/04/2015	Quiz 1	Sally	10	95
25/04/2015	Quiz 1	Richard	10	91
26/04/2015	Quiz 1	Thomas	10	79
30/04/2015	Quiz 2	Sally	15	97
01/05/2015	Quiz 1	Jane	10	71
10/05/2015	Quiz 2	Richard	15	86
11/05/2015	Quiz 2	Thomas	15	91
30/05/2015	Quiz 3	Sally	20	92

Table 20.2 Example of students' postings to forums

Date	Student	Messages posted
05/06/2015	Thomas	Re: difference between database types
04/06/2015	Jane	Re: difference between database types
02/06/2015	Richard	Difference between database types
25/05/2015	Thomas	Re: discussion about relational databases
24/05/2015	Sally	Re: discussion about relational databases
23/05/2015	Jane	Re: discussion about relational databases
22/05/2015	Sally	Re: discussion about relational databases
18/05/2015	Thomas	Re: discussion about relational databases
16/05/2015	Sally	Discussion about relational databases
25/04/2015	Richard	Re: question about Quiz 2
23/04/2015	Sally	Re: question about Quiz 2
23/04/2015	Jane	Re: question about Quiz 2
20/04/2015	Sally	Question about Quiz 2
02/04/2015	Jane	Re: introduction
01/04/2015	Richard	Re: introduction
01/04/2015	Sally	Introduction

course for three months (April to June) and have had different forum posting activities, as shown in Table 20.2. Awards are configurable so that a teacher can decide what thresholds are used to determine the requirements on when an award is given to students. For example, some courses might require many posts, while other courses might not. By changing the settings, a teacher can tailor the motivational technique to the course. Let us assume that in this case, we go with the default thresholds, which are five postings per month for a gold award, three postings per month for a silver award and two postings per month for a bronze award. To calculate the awards, the number of posts a learner has written in each month is considered and then, the awards given to students are displayed. Furthermore, a total score is calculated that represents the learners' overall number of points achieved for each award based on the weight of the awards, which can again be configured by teachers. Given the actions in Table 20.2, Sally would see the awards page as depicted in Fig. 20.5.

20.5 Conclusions

This paper introduced the design, implementation and verification of four motivational techniques: progress timeline, progress annotations, rankings and awards, as well as a tracking mechanism to log students' behaviour related to these techniques. The motivational techniques are designed to be used in different courses and learning systems; however, they were implemented as a block in Moodle.

By integrating multiple motivational techniques into learning systems, students can select between different techniques that can increase their motivation at different stages and in different situations in the course. Furthermore, by tracking how students use these motivational techniques, we can get valuable insights into when and for whom each motivational technique is most valuable in terms of motivating students most. Such information is the basis for creating an adaptive system that can provide students with the right motivational technique at the right time based on the students' individual characteristics and their current situation in the course.

Future work will deal with the use of the motivational techniques and the gathering of data to assess which students use which techniques in which situations. Based on this information, an adaptive mechanism will be developed that suggests motivational technique to learners based on their characteristics and situations in the course.

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Chapter 21
A Proposed Model for Creating Authentic Learning Objects for Indigenous Learners

John Loewen, David Loewen, Kinshuk and Jarkko Suhonen

Abstract Today's educational environment is based on a very Eurocentric approach, which many Indigenous learners find as culturally irrelevant. This paper posits potential uses of information communication technology (ICT) as components of culturally and community relevant, and collaboratively developed learning tools, with the potential to provide authentic and relevant learning experiences for Indigenous learners. Additionally, through collaborative development, these ICT tools may function as valuable and essential interfaces between contested and often different worldviews and educational purposes. To do this, however, requires some wading into frequently contested spaces surrounding standard formal Eurocentric educational settings and the highly varied, place-specific, and community-specific landscape of Indigenous knowledge (IK). Aspects of this contested space are explored in this paper to provide some context. The focus of this paper is on the potential for collaboratively developed ICT learning tools to serve as a possible interface between Western, often Eurocentric knowledge, and IK as well as providing authentic and relevant learning.

Keywords Authentic learning · Indigenous knowledge · Fuzzy logic · ICT

21.1 Introduction

The educational systems currently encountered by many Indigenous learners are culturally irrelevant, leading to a distinct lack of enthusiasm for many of these learners worldwide [1]. Exacerbating this issue, for most Indigenous learners,

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historical evidence indicates that formal education has been dominated by either churches or governments and guided by an education philosophy rooted in ideology rather than pedagogy [2]. There is also a long history of colonization in many Indigenous communities resulting in imposed education systems often in the form of residential or boarding schools that resulted in a litany of abuses, and now intergenerational trauma. The result of this is that many Indigenous people identify formal education as a negative process, as a deliberate way to minimize their languages, cultures, and distinct knowledge. This paper identifies some differences between Indigenous ways of thinking and knowing and Western "Eurocentric" ways of knowing in order to identify potential interfaces between them and thus providing authentic learning for Indigenous learners. From this brief exploration of knowledge systems, a model for authentic learning is provided and further validated through a case study example that instantiates the model in a culturally relevant learning environment.

21.2 Indigenous Knowledge and Western Knowledge: Is There a "Common Ground" Interface?

Indigenous knowledge (IK) (often referred to as traditional knowledge, local knowledge, traditional ecological knowledge, etc.) is a way of life, not an occupation or interest. IK also resists specific definitions, as it is a fluid process, more than a defined thing and varies from community to community. IK includes both the process of knowing and the knowledge itself [3] and it is experientially grounded [1]. Many refer to this idea as a holistic way of thinking, or "holism." Often, IK about the natural world contrasts sharply with Western scientific knowledge in a number of ways [4], yet IK does not exist in an "either/or" dichotomy with Western knowledge and there are dangers in identifying them as such as this may establish superior–inferior relationships [5]. This tends to support more of a both/and perspective as opposed to an either/or perspective. With this in mind, [6] state that there is an urgent need to bridge different knowledge traditions, to devise methodologies that allow us to work effectively between these traditions. So, the question arises "how can this be done?" Recent advances in qualitative software for use in IK research, in agent-based, and AI software that provides reasoning capabilities (for example, fuzzy logic) suggest some possible ways of bridging these two very different knowledge systems [6]. In the cases of IK and fuzzy logic, the analysis of the complex system behavior is carried out, not by using numerically precise data, but by using language-based data that are qualitative and rich [3]. Combining these ideas with ways in which ICT has been shown to be an effective tool for Indigenous learners may be the key to creating learning opportunities for Indigenous learners that are both pedagogically and culturally relevant. Understanding local culture and knowledge is a key component, and any ICT system that is developed must be relevant to local needs, which need to be defined by local people and communities. Formalizing a way in which IK, or local knowledge and computational knowledge may be integrated to make sense of the world as approached by a holistic thinking culture is of great utility. Some guidance on a potential first step is provided by [3], stating that the co-production of knowledge is a useful way forward and that this knowledge production should always be preceded by trust building and the development of working relationships with knowledge holders (step 1 in Fig. 21.1). With that in mind, a next logical step is to identify who will be involved in this co-production of knowledge, namely the participants, collaborators, and contributors. In this case, they include learners, educators, knowledge holders and sharers, and community leaders. Educators must have experience teaching in non-traditional environments where the emphasis is on providing contextual and authentic learning opportunities, and they must understand the process of emergent learning which includes a multi- and interdisciplinary approach. Knowledge holders, knowledge sharers, and community leaders play an integral role in the knowledge generation process, which in order to acquire a depth of knowledge, may be time-consuming and intensive. The next step is the knowledge co-production process. Methods that have been shown to be successful in this domain include, for example, participatory techniques following a community of practice learning approach [7]. This helps ensure that the epistemology and pedagogy are congruent with community needs. Once the knowledge gathering process has commenced, it is then important to address the way in which this knowledge is organized and stored for the purpose of dissemination and retrieval within a culturally relevant learning system. For example, use of IMS LD Level B allows for the ability to present learning objects to the

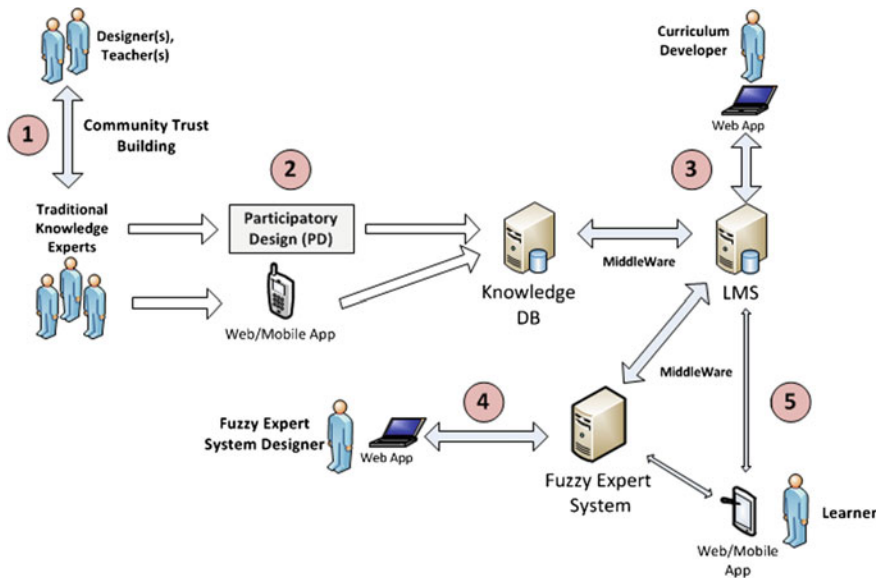

Fig. 21.1 Diagram of proposed model

user at run time (using IF…THEN…ELSE logic, similar to fuzzy logic rulesets) according to the preferences provided by the user [8].

Lastly, a visual simulation tool that provides a sense of place, shown by [9] to be beneficial to Indigenous communities, is created (as shown in Step 5 of Fig. 21.1) to allow learners to provide inputs based on the knowledge acquired during the PD phase. To show proof of concept of this model, a case study is now provided.

21.2.1 Case Study—Salmon and the Carrier People

When speaking of the Nakaztli people, [10] identified that the life cycle of the salmon was entrenched into the life cycle of the Nakaztli community. A bad harvest of salmon would directly affect the economic well-being of an individual, family, and community. To illustrate the differences in context between communities, this was not the case for the Sekani people (whose traditional lands are roughly to the northeast of the Nakaztli), who disdained fish of any kind [10]. Therefore, any culturally relevant learning system must take into account potential major local differences between communities. The purpose of this case study is to show how ICT may be leveraged to provide a holistic thinking learning tool that, according to the inputs provided by learner, simulates the effects of salmon harvest health on the well-being of a community. In order to simulate a holistic approach, all of the factors that affect the health of a seasonal salmon harvest (in our model, called attributes) as determined through collaboration with community and community experts. These factors are assigned weights (from 0 to 1) according to their importance as determined by the experts. Example attributes in this case study include catch-per-unit effort, season, and weather. From this set of attributes, fuzzy logic is used to create rules according to the inputs in the form of fuzzy logic rulesets. This process is shown in step 4 of Fig. 21.1. The fuzzy logic rulesets are combined to produce an output, in this case, harvest health. This process forms the foundation of the fuzzy logic simulator (the expert system). Each linguistic value of the output has an associated learning object(s) or module(s). In this way, multiple outputs may also have associated rulesets that may be combined for further simulation. From a ruleset (referred to as multiple ruleset aggregation), a fuzzy rule base may be created that acts as the inference engine which steps through the heuristic rulesets one by one (shown in Fig. 21.2).

The result is a quantitative value that is mapped to quantitative value that represents a qualitative value for “harvest health.” Linking this back to the original research question, to providing a possible interface between two ways of thinking, the ability to represent qualitative thinking using fuzzy logic, and to combine representations of qualitative thinking in a quantitative manner, similar to that of the work of [11], we can simulate a holistic model using ICT. The resulting “de-fuzzified” qualitative value(s) represent holistic thought and allow for the retrieval of authentic learning objects, objects that have been created using a community of practice learning approach. Having identified the importance of this

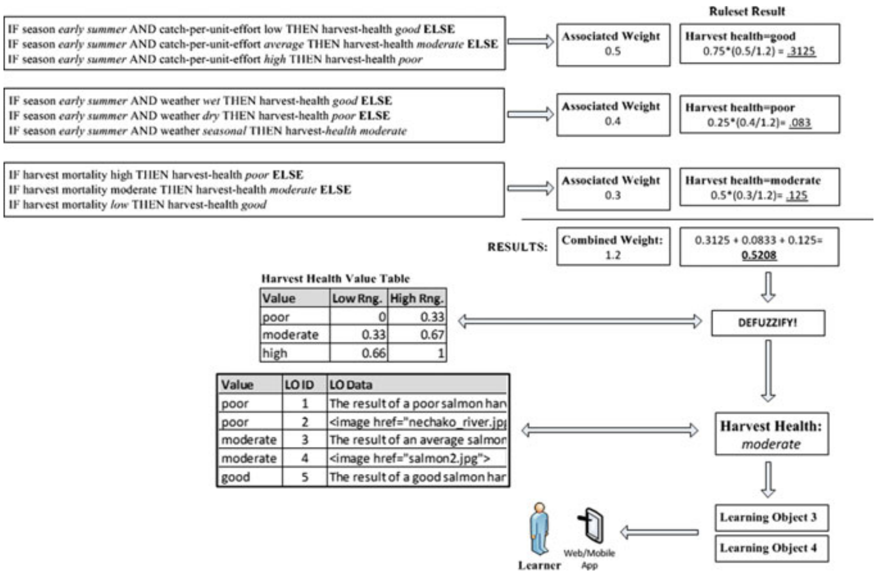

Fig. 21.2 Example of multiple ruleset aggregation

approach [7], add that the instructional design of educational programs must use the skills and values of the community, its cultural traditions and its problems and issues in order to create a unified and authentic learning environment.

21.3 Discussion

Through the preceding case study, we have demonstrated that authentic learning may occur through knowledge gathering, dissemination, and learning object design. The authentic learning objects created through the development process may vary greatly from community to community; authentic learning toward a particular subject or object may contrast greatly from one community to the next. The significance to these observations and findings is that if authentic learning is desired, it provides credence to the model of designing learning with community involvement at the forefront. As [3] state, "Indigenous knowledge holders do not need fuzzy logic to understand holism; they already practice it." The value of using ICT as a tool is that many different learning opportunities may be created in a short period of time by running simulations with varying inputs. In this way, the learner is able to see, for example, the effects that each factor may have on the health of a particular harvest of salmon and consequently how that may affect the overall health (simulating a holistic approach) of the community. Authentic learning is provided by the inclusion of the representation of the effects of harvest health as determined by knowledgeable community members. Additionally, other members of a community, those who are not the expert holders of knowledge have a tool that interfaces to this knowledge in an interactive and easily accessible way. Lastly, following the prescribed model allows for iterative design, ensuring that previously created learning objects and tools may be built on (e.g., multiple ruleset aggregation), added to, and improved as the design process progresses.

21.4 Conclusion

We recognize that there often exists an inherent tension between these two ways of thinking, and we argue that in many situations, the underlying foundation of education is not relevant for Indigenous learners. This research opens up new ways for IK to be preserved and represented in culturally relevant scenarios for each community. As [7] observe, subject matter that is relevant to these communities must be taught. We are proposing a model that may be used as a starting point from which authentic, relevant learning objects may be created. From an additional research perspective, in order to reach the largest audience, standardization needs to be considered to provide possibilities for reusability. In this context, this need is, however, a double edged sword. As [6] state, "the advancement of a standard approach may be a cul-de-sac, given the remarkable diversity of knowledge traditions worldwide, their internal variations relating to individuals multiple understandings, and their constant revision over time." Issues identified when addressing the research questions include the initial setup of the framework and of the knowledge data, which are both labor and time intensive, such as is the case for any system that does AI modeling and simulation. Additionally, teachers will need to be educated on how to use the tools and how to create the appropriate learning objects for the subject matter. Future work may include research on approaches to imparting knowledge to the teachers/educators of the learners in this model, as well as the creation of tools based on this model that allow for the creation of authentic learning objects for Indigenous learners.

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Chapter 22
An Embodied Design with Collective Intelligence for Creating Interactive Video Lectures

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Abstract In pursuit of quality learning, instructors continually strive to improve learning designs and apply appropriate learning strategies correspondingly. At the same time, a variety of lecture types are emerging, owing to the advances of information and communication technologies. Recently, flipped classroom and Massive Open Online Course (MOOC) have gained popularity as learning models because of their learner-centered and interactive focus. Interactive video lectures play an important role of these learning models and have also started to rise prominence by means of meaningful interactions for getting better learners' comprehension when watching the learning content. Hence, this study proposes a new approach to create interactive video lectures by exploiting the power of collective intelligence and the features of natural user interaction.

Keywords Embodied design · Interactive video lecture · Collective intelligence · Natural user interface · Scaffolding functions

22.1 Introduction

Interactive video lectures are increasingly drawing people's attention and are being gradually adopted in online asynchronous learning and electronic textbooks because of high interactivity during the learning period. Compared with reading-based content, video lectures with higher media richness can facilitate learners to comprehend

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complicated learning concepts and improve their learning performance [1, 2]. The literature also suggests learners would demand richer and more interactive learning experience than just learning individually with video lectures [3]. When learners have trouble comprehending the video lecture, a common way is to use the related discussion forum for obtaining additional support, but the searching process indeed takes time. Thoughts and interactions from many participants which are refined and accumulated in a discussion forum become collective intelligence (CI). By well exploiting the CI, various interactive learning activities can accompany multiple types of interactions. Based on the perspective of embodied cognition, human body situated in a richly perceived environment plays a crucial role in creating and extending cognition [4, 5]. Embodied experience situated in a richly perceived learning environment is capable of expressing and exemplifying abstract concepts into natural user interactions, such as speaking and motions. The cognitive process consequently incorporates with the involvement of external bodily reactions as learning clues for knowledge construction. Hence, creating interactive video lectures with the selected content based on CI and interactions via embodied experience has the potential to help learners to obtain better learning outcomes.

22.2 The Design of Embodied Interactive Video Lectures

The framework of embodied interactive video lecture (Fig. 22.1) is composed of six parts including technology, theoretical foundation, content from CI, interactive learning activity, video-based content, and target learner. *Technology* comprises of a computer with a display, a microphone array, and a motion-sensing input device to build a fundamental base for natural and direct interactions such as speech and gesture recognition. *Theoretical foundation* is based on embodied cognition, situated learning, and scaffolding functions to design interactive learning activities effectively for learners. *Content from collective intelligence* extracted and reused from a video lecture discussion forum is the body of the interactive learning activities. *Interactive learning activity* provides the activity entity with the content from CI that learners can actually perform in a learning environment. *Video-based*

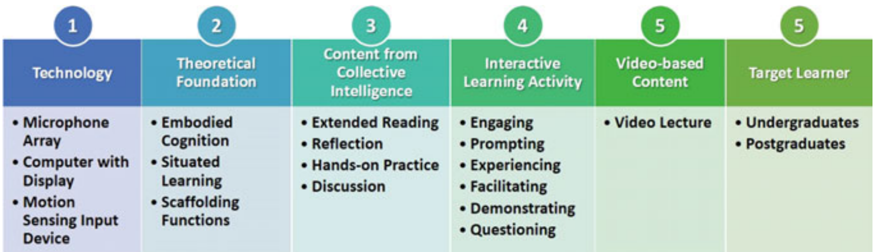

Fig. 22.1 The framework of the embodied interactive video lecture

Fig. 22.2 A selection approach to exploit content from CI for interactive learning activities

content is the main part of the electronic lecture. *Target learner* then can watch and learn from an interactive video lecture including the video-based content and the interactive learning activities. This design is to provide learners meaningful resources as interactive learning activities when watching a video lecture and enable learners to have embodied experience (e.g., using speaking and bodily motions as clues) for knowledge construction when performing the activities.

For interactive video lectures, the content of interactive learning activities and the method of how learners perform those activities play a crucial role to determine how well learners comprehend the content and construct knowledge. This study selected appropriate content from CI in a video lecture discussion forum by two approaches, namely *top rated posts* and *most replied posts* (Fig. 22.2). After extracting the appropriate content, it can be redesigned as interactive learning activities and learners can perform these content-related activities through speaking and bodily motions.

22.3 Examples of Interactive Learning Activities

The interactive learning activities comprise of six forms based on six scaffolding functions, namely engaging, prompting, experiencing, facilitating, demonstrating, and questioning (Table 22.1).

When learners watch embodied interactive video lectures, they interact with two kinds of characters (i.e., audience and instructor) via speaking and bodily motions. In the beginning, learners can see a basic layout regarding the information of playing progress and player status (Fig. 22.3).

Table 22.1 Six interactive learning activities of the embodied interactive video lecture

Type	Scaffolding function	Description
1. Engaging	Recruitment	An *audience* actively encourages the *learner* with a prologue or expresses motivation for the content. Then, the *learner* makes a simple response to the *audience.*
2. Prompting	Reduction in degrees of freedom	An *audience* actively asks the learner a question for reflection, and the *learner* has 30 s to think about it. Then, the *audience* provides a thought related to the question.
3. Experiencing	Direction maintenance	The *learner* performs a tiny exercise or a simple simulation related to the content with the guidance of an *instructor.*
4. Facilitating	Marking critical features	An *instructor* actively provides crucial concepts to the *learner* when learning.
5. Demonstrating	Demonstration	An *instructor* provides an example, ideal case, or solution for describing a concept, and the *learner* can strengthen the impressions on the learning concept.
6. Questioning	Frustration control	The *learner* can ask an *instructor* for assistance from a set of selected questions receive a corresponding answer when being in trouble with learning.

Note The "audience" and "instructor" are the characters in embodied interactive learning activities. The "learner" is the person watches the embodied interactive video lecture

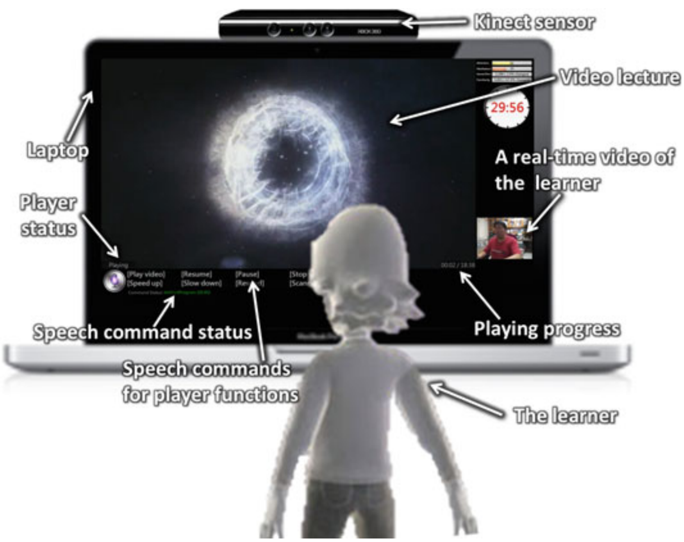

Fig. 22.3 A basic layout when watching an embodied interactive video lecture

Fig. 22.4 The embodied design of interactive learning activities: **a** Prompting. **b** Experiencing

At the bottom of the screen, various available options can be used via voice communication with a microphone array or gesture movements with motion sensors. These available options offer the learner pre-designed and meaningful responses to the characters of an audience and an instructor. The content of the available options and what the characters said have been extracted and refined from CI. Then, the learner can perform a series of interactive learning activities. When the interactive learning activities are in progress, the embodied interactive video lecture is automatically paused. Figure 22.4a, b shows how the *prompting* and *experiencing* of interactive learning activities work during the watching period. The learner directly interacts with the audience by speaking and performs a specified movement with body experience for helping comprehend an abstract concept when watching.

22.4 Conclusion

This paper has proposed the design of embodied interactive video lectures and given a brief account based on a systematical approach for creating interactive video lectures by exploiting the power of CI and the features of natural user interaction. As of now, a workable learning system with the Kinect sensor is able to successfully recognize learners' speech and movements when they watch a embodied interactive video lecture and perform corresponding interactive learning activities. Next, an experiment will be conducted to evaluate the effects of the embodied interactive lecture on learners' learning outcomes.

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Chapter 23
Collaborative Learning through Creative Video Composition on Distributed User Interfaces

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Abstract We report two studies that fed into user-centred design for pedagogical and technological scaffolds for social, constructive learning through creative, collaborative, reflective video composition. The studies validated this learning approach and verified the utility and usability of an initial prototype (scaffold) built to support it. However, challenges in interaction with the target technology, multi-touch tabletops, impacted ability to carry out prescribed learning activities. Our findings point to the need to investigate an alternative approach and informed redesign of our scaffolds. We propose coupling of distributed user interfaces, using mobile devices to access large, shared displays, to augment capability to follow our constructive learning process. We discuss also the need to manage recognised challenges to collaboration with a distributed approach.

Keywords CSCL · Creative video composition · Reflective knowledge construction · Shared displays · Distributed UIs · Process support

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23.1 Introduction

We describe research effort in an EU project that aims to explore how the process of production and reuse of digital video content can be harnessed to overcome barriers to conceptual understanding of STEM (Science, Technology, Engineering, and Mathematics) topics. The project is grounded on a specific pedagogic framework that aims to identify "*threshold concepts*" (TCs) [1]—key concepts that constitute learning barriers—and facilitate understanding through the creation and sharing of explanatory, expressive, student-managed videos. These, with additional data, such as quizzes and peer comments, and subsequent engagement with viewers via interactive public displays constitute what we call a "*video performance*" [2].

We explore how software designed to augment reflective, collaborative video composition on shared, multi-touch surfaces promotes colocated, collaborative knowledge construction within a prescribed learning process. By encouraging target users to *inform* the design process [3] we identified challenges in interaction during early evaluation of this technological and pedagogical scaffold; we explore further design to ensure fluid collaboration and, therefore, deep, reflective learning [4]. We envisage, through this process, to build more effective scaffolds for collaborative knowledge discovery and construction, review and consolidation.

We present, first, our research objectives and the methodology followed and then discuss the outcomes of our studies. We conclude with pointers to redesign of our scaffolds, taking into consideration learning and guidelines from related work.

23.2 Research Objectives

Our aim, illustrated in Fig. 23.1, is to build scaffolds that augment the construction of deep, shared, conceptual understanding. Our approach harnesses collaborative story creation, performance and video-making as a way to foster creativity and

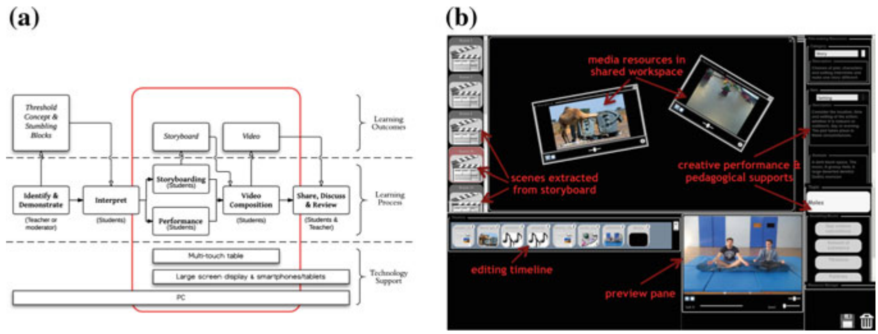

Fig. 23.1 Technological and pedagogical scaffolds for collaborative, reflective learning. Additional, detailed snapshots of the UI may be found at http://bit.ly/1SUIRCc. **a** Process flow and architecture. **b** Video composition workspace

curiosity, engender alternative, visual thinking and maintain engagement as students explore preidentified stumbling blocks to understanding of TCs in STEM. Students are guided to craft stories that *juxtapose* TCs against alternative, creative, real-world or other experiences they relate to. Doing this through performance and video-making requires students to step through a process of collaborative knowledge discovery and construction, leading to deep, correct understanding of a TC and its component parts [1, 2, 4, 5]. Further, the resultant video serves as a tangible artefact and expression of understanding, and an avenue for further reflection on, and hence, reinforcement of any knowledge gained.

Longitudinal studies with a variety of students and teachers have provided empirical evidence that confirms research pointing to the potential in our approach to social, constructivist learning [2, 4]. We follow a user-centred design methodology, examining options for building pedagogical and technological scaffolds for students and also the teachers or orchestrators of learning activities in typical classrooms and more flexible learning environments. Building on research in Computer-Supported Collaborative Learning (CSCL), we started with a premise of technological support for colocated, collaborative learning activities around large, shared, multi-touch tables. This was to harness recognised benefits exhibited in intuitive, active, enthusiastic, tangible interaction within groups around tables [4, 6–10]. This leads to our initial research question:

> Is interaction around a large, shared, multi-touch table sufficient in itself as an enabler for augmented, collaborative, reflective construction of understanding?

Existing studies ([6, 7, 9], among others) confirm the merits of this initial proposal to support collaborative learning around multi-touch tables. However, collaboration comes with its own challenges, including conflict due to group dynamics, ensuring equitable contribution, effectively supporting distributed tasks and transitioning back to whole group activity—challenges that may be compounded by limitations in the supporting technology [4, 7, 10]. These must be carefully managed, to ensure they do not outweigh the benefits of CSCL. Other practical considerations, associated specifically with reliance on digital touchtables, include still very high financial cost, low portability due to physical size and weight and, hence, limitations in scalability of tabletop-based solutions for CSCL. Orientation of the display, combined with table size, presents further challenges for interaction, which may exclude users with physical and learning disabilities.

To be successful in meeting our goal—to enable deep, conceptual understanding, we must ensure a practicable solution that fosters reflective, collaborative knowledge construction, without increasing learners' cognitive load [10]. We present, in Sect. 23.3, our methodology for exploring this initial proposal.

23.3 Methodology

The introduction of *Information and Communication Technology* into the classroom is increasingly commonplace, especially for inquiry-based teaching and learning, as is often used in STEM [11, 12]. This is due largely to wide availability and affordability of personal computers (PCs) and now, also, small, personal devices such as smartphones and tablets [13, 14]. Interactive whiteboards, often with custom learning software, are gradually replacing traditional classroom blackboards [15]. Studies show that multi-touch tables, a variant of large displays, foster collaboration, supporting social, interactive learning [4, 9]. Touchtables are, however, still regarded as relatively new and less accessible technology [6, 7, 10].

While studies such as in [5] provide evidence for the merit in our constructive learning approach, driven by creative, collaborative video-making, we must still provide evidence for its utility and applicability, along with intuitive support for implementation within established/traditional learning structures and institutions, if we are to see adoption in practice [11, 12]. A key component of our design is therefore to involve a good cross section of our target users (students and teachers) as informants to the system and user interface (UI) design (see [3]) and through a process of iterative usability evaluation.

We focus on two design studies, in Sects. 23.3.1 and 23.3.3, with secondary school and postgraduate students, respectively. We restrict our discussion to participants' interaction with the technology for two key steps in our learning process, highlighted within the red frame in Fig. 23.1a: (1) the *interpretation/understanding* gained during ***storyboarding***, as students craft their initial story ideas and (2) the *reflection* engendered as they ***compose*** a final video that expresses creatively the understanding gained through this process. All user sessions were video- and audio-recorded, to supplement researchers' observations captured in written notes.

23.3.1 Case Study I: Design Sessions with Secondary Level Pupils

We carried out initial and follow-up studies, in July 2013 and 2014, with a key target user group: 15–16-year-olds at a stakeholder school in England (just after completion of the "General Certificate of Secondary Education" examination), to inform the design of the initial prototype (see Sect. 23.3.2). Participants followed the learning process from storyboard creation through to performance, filming and video composition (some sessions ended just short of producing a final video), on a teacher-selected topic. The aim was twofold: (1) to provide initial assessment and verification of the learning process itself (Fig. 23.1a) and (2) to trigger design ideas for the technological scaffold required for effective task completion.

Storyboarding (planning/interpretation) was carried out on paper templates (size A3) on flat, physical surfaces. In the first study, with 13 participants in two groups, one carried out the video composition activity on a multi-touch tabletop, using a medium-fidelity [6] video browsing prototype. The second used Apple's *iMovie*,[1] from a MacBook Pro with its display projected onto a wall. In the follow-up study, with 17 participants in five groups, video composition was carried out on a shared desktop or laptop (screen size 15.4/17 in.). Four used TechSmith's *Camtasia*[2] and one, iMovie. In addition to the first two goals, this study sought concrete measures of the resources—time and technological support—required for implementation within the regular classroom schedule and environment. Using commonly available software and hardware further provided a baseline from which to measure added value in following our learning process.

23.3.2 Initial Touchtable-Based Prototype

Guided by the outcomes of the design studies in Sect. 23.3.1, a number of subsequent studies following the same methodology in a variety of formal and non-traditional learning environments and earlier studies with teachers/instructors (see also [2, 4]), we carried out further, comprehensive analysis of the CSCL literature. This extended requirements and design phase resulted in an initial prototype targeted at the multi-user, multi-touch table, implemented using the *Microsoft Surface 2.0 SDK*. This has been tested on the *Samsung SUR40* touchtable with *PixelSense*[3] and on laptops running the Surface emulator in Win 7 & 8.

Figure 23.1a maps stages in the learning process to key components in the prototype and the supporting technology envisaged. Two main modules are available that make use predominantly of *drag-and-drop* interaction in a highly visual interface: **storyboarding,** built to reflect a traditional storyboard template, with additional support for attaching electronic resources to scenes; **video composition** (see Fig. 23.1b), which may be initialised from a storyboard, to persist backward, also, subsequent modifications to the storyline. The aim is to provide both process support and enable reuse of the knowledge artefacts thus created.

Support for parallel, subgroup activity includes extracting individual scenes and resources to transient spaces etched out of the shared workspace. Simple means for capturing notes, storyline and resource metadata, and seamless tagging of elements allows such information to be persisted through to production of the final video. We describe briefly, in Sect. 23.3.3, its initial evaluation.

[1] http://www.apple.com/uk/ilife/imovie

[2] http://www.techsmith.com/camtasia.html

[3] https://msdn.microsoft.com/en-us/library/ff727815.aspx; http://www.microsoft.com/en-us/pixelsense/whatsnew.aspx

23.3.3 Case Study II: Design Sessions with University Students

This study, in January 2015, aimed to assess where the UI design and underlying system functionality for the prototype (scaffold), described in Sect. 23.3.2, foster knowledge discovery and capture during video-making. The evaluation also looked particularly at the impact of the target device (the multi-touch table) on collaboration, and hence, deep, reflective learning. The participants were masters level media technology students at a Swedish University, acting as (domain) expert reviewers. In the first session seven participants were given an overview of the learning process (Fig. 23.1a). They then carried out a short storyboarding exercise on the tabletop, guided by a topic about which a subset had some knowledge. Using the custom conversion facility, the storyboard was used to populate the initial view of the video editing timeline. The participants carried out an inspection of the video composition workspace, to identify additional requirements and functionality, beyond the technical requirements for producing a video, to support continued (collaborative) reflection and knowledge construction.

A follow-up session with five participants (four from the first session) reviewed an update to the UI (in Fig. 23.1b), based on feedback to this point. This focused on the video composition activity and the following step in the learning process: sharing of student videos and soliciting feedback via public, large screen displays coupled with smaller, mobile devices (smartphones and tablets). The study concluded with a brainstorming session in which the participants, based on their domain expertise, gave an assessment of where they saw added value as a pedagogical scaffold, over traditional video editing tools. To address interaction issues on the tabletop, we asked them to consider requirements for alternative technological support, including reuse of the (distributed) set-up for the sharing phase. We discuss our findings and the implications for further work in Sects. 23.4 and 23.6.

23.4 Discussion

A key aspect of our learning approach is to harness collaborative knowledge construction as a trigger for peer and reflective learning. Evaluation with students, with a good degree of variation in level of study, learning environment and group dynamics, has validated this creative learning process (see also [2, 5]), confirming also existing research in social, constructive learning, especially where supported by dedicated technological scaffolds [8, 12–15].

To ensure that these benefits translate in practice, we revisit key observations across the two studies reported in this paper, supported also by other relevant project studies. To answer our research question (in Sect. 23.2)—to what extent interaction with the pedagogical and technological scaffolds on a shared, multi-touch table meets the requirements of student groups following our process—we examine also practical requirements for implementation in the classroom. We address elements that participants recognised to (1) foster effective collaboration, thereby augmenting capability for (2) achieving learning goals, and (3) for carrying out the technical tasks involved in this process, for crafting and then translating their story ideas into an expressive video, and (4) finally, sharing the outcomes with their peers. We also highlight where the use of these scaffolds was hampered.

23.4.1 Key Findings

Fostering Collaboration Storyboarding stands out, across all user studies, as the activity in which a high degree of collaboration was initiated and maintained, as students worked together to break down the learning topic and collect and ***reflect*** on the knowledge and resources that would contribute to their stories. With respect to interaction, the practicalities of editing a paper storyboard led each group to appoint a *scribe* at the start, while the others mainly contributed to the discussion. On the tabletop, however, the initial response was for most of the group to attempt to interact with the UI at the same time. However, even with the larger workspace, and also because of delayed responsiveness of the hardware, participants found that they got in each other's way (see also [7, 9, 10]). The group concluded that they would have to take turns or appoint a "secretary" if they were to make optimal use of the (digital) workspace.

Meeting Learning Goals The video produced serves as a tangible outcome of the collaborative learning activity. However, as reiterated in [2, 4], the ***process*** involved in reaching this goal is where true learning is obtained. We have evaluated support for the video composition activity from three perspectives: (1) using traditional video editing tools: (a) from a large, shared display obtained by projecting from a laptop onto a wall; (b) around (single-user) PCs or laptops; (2) using the prototypes developed for the multi-touch table. From a pedagogical standpoint, option (1b) can be discounted; confronted with a technical tool on single-user machines, the activity was treated as a technical task, in which mainly group members with prior technical know-how participated. Collaboration almost completely broke down, and with it, the valuable reflection on and reinforcement of new knowledge gained as well as the identification and correction of misconceptions, that was seen in the other two settings (a similar outcome is reported in [9]). Increasing the physical workspace in option (1a), by projecting onto a wall, increased usability as a shared resource. Here, even still working with a technical video editing tool, active discussion and joint reflection on the knowledge content drove the activity. Finally, in addition to custom support for accessing topic-specific learning material in option (2), a key benefit seen was explicit support for persisting information collected at each stage throughout the process. The table comfortably accommodated seven adults (upper limit tested, average was three to four). As in (1a), the large, shared view engendered active discussion. However, this was handicapped by inability to take full advantage of the simultaneous, multi-user interaction that was a driver in proposing the multi-touch table as the target device.

Sharing and Soliciting Feedback Technological support for the ***sharing*** stage in the learning process builds on studies in [2]. These solicited requirements for encouraging serendipitous collaboration between peers and students who would not normally interact with each other, by situating large displays playing the student videos in public spaces. The aim was to draw passing students to engage with the educational content using a public controller for the video stream, or extend the shared space to their personal smartphones or tablets, to allow further interaction, e.g. posting and receiving personalised feedback. Following on the advantages seen in persisting knowledge content across the video-making activities, participants recognised value in sharing also, beyond these public spaces, the interim artefacts (e.g. storyboards, video clips) as reusable learning resources.

23.4.2 Design Implications

These outcomes revalidate our learning process, but reinforce the need for custom scaffolds to harness its full potential. They also highlight challenges for adoption and therefore the need to revisit the proposed technological scaffold. Considering the challenges experienced in multi-user interaction with the touchtable, the cost of acquisition and installation becomes even more significant. On the other hand, participants saw potential in extending the distributed set-up for sharing videos in public spaces as a means to optimise especially the video composition activity, which has greater distribution of subtasks. Based on our observations of student interaction in the different settings and design ideas triggered by the discussions:

> Would a distributed approach, utilising smaller, more accessible, portable, touch devices, coupled with a large, shared display, maintain collaboration, and therefore, augment reflective construction of understanding?

To answer this (revised) question, we reviewed responses to the questions that guided the semi-structured debrief and brainstorming sessions that concluded each design study. Because this work is exploratory, we focus on the rich, qualitative information collected, complemented by records of each session. Guided by this, we carry out further investigation of relevant work (in Sect. 23.5), before concluding with pointers to redesign. We aim to keep cost—financial, development effort and path to adoption—low by reusing easily accessible technology. However, we must still develop novel, alternative approaches that engender and maintain collaboration while using a coupled, albeit distributed, set-up.

23.5 Related Work

To increase confidence in adoption of our approach, especially in formal learning environments, we must provide both a theoretical foundation that validates it and practical, customisable, pedagogical and technological scaffolds that allow teachers to integrate these into the classroom. Therefore, we look at examples of the use of large, shared displays to foster collaboration. Dillenbourg and Evans [7] discuss the merits of colocated collaboration around tabletops, but also caution over expectation of what is still relatively new technology. They propose a number of recommendations for optimising the use of touchtables in collaborative learning. Yuill and Rogers [10], similarly, caution the notion that interaction around shared tabletops automatically leads to natural or seamless collaboration.

It is imperative that we do not simply replace the interaction issues faced on multi-touch tables with a different set of challenges. Rogers and Lindley [9] compare interaction on horizontal and vertical displays in an information seeking task: in isolation, horizontal displays led to more exploration, due to more natural turntaking and diversity in information examined. However, working with them was seen to be less structured than with vertical displays. Importantly, complex activity requiring interaction with a shared display and other information artefacts (e.g. paper) was most effective when physical layout and constraints simplified transition between devices and increased awareness of other parallel activities. This gels with [11], where replacing a fixed PC with a tablet increased an instructor's flexibility, moving about a classroom, to assist problem-solving activities.

Other studies employ more widely available technology, such as interactive whiteboards and large monitors attached to PCs, to increase space for collaborative problem-solving [15]. Liu et al. [14] investigate the role of a large screen display in augmenting functionality in mobile devices; the shared workspace facilitated communication during collaborative learning, leading to significantly more interaction and discussion among students. Lamberty et al. [8] report a study in which classmates shared visual mathematical artefacts describing new concepts, by projecting from their PCs onto a large screen. As in [4, 10, 11], knowing their solutions were intended for a wider audience, learners were more conscious of content and presentation. This also piqued interest in other groups' work, providing additional benefit from the exercise. This mirrors comments in a number of our studies as participants built and reflected on their stories to ensure that they would appeal to and engage their peers, in addition to teaching about the TC.

Our studies have given us insight into the affordances of various settings for technological support. Comparing with the baseline—traditional video editing software on single-user PCs—reinforced the potential in our creative learning process. However, this potential will only be realised if it is accompanied by practical scaffolds that enable effective adoption and truly augment learning. The studies we report enabled us to collect valuable design ideas for these scaffolds and recognise also limitations in our initial proposal, based on interaction around multi-user, multi-touch tables. Continued research points to a novel approach to this challenge: employing a more distributed environment, but centred around a large, shared, digital workspace, to which smaller, personal and shared touch devices are coupled, to continue to foster the tangible collaboration that is key to our constructive learning approach. We conclude with our revised proposal.

23.6 Conclusions and Future Work

The ideal scenario would employ a set-up that allows the collaboration fostered at the start of the creative video-making process to be extended through to the final sharing phase. Empirical evidence and research demonstrate correlation between fluid, equitable, collaborative knowledge discovery and problem-solving [5, 10, 15], and joint reflection on the knowledge thus discovered [4], a process that results in turn in consolidation of, and therefore, deep, conceptual understanding. While a more distributed approach addresses requirements for portability and affordability, and is particularly useful for synchronous, subgroup tasks [8], working on devices designed for individual use comes with the danger of lowered awareness of other parallel activities [9] and disengagement from the shared task. Our revised design comprises a large screen for sharing and maintaining awareness of peer (group) work, synced with PCs, smartphones and tablets serving as input devices and for parallel, subgroup tasks during the creative video-making (storyboarding and video composition). Existing work shows that in such distributed environments, being able to recognise, even in the periphery, other contributors' work helps to maintain awareness of the shared task and results in an increase in interaction [8, 14]. Our proposal therefore includes support for communication between all devices via the shared, central device, to facilitate collaboration. Participants also suggested avatars on the shared screen, to simplify recognition of and access to others' work, analogous to peering over their shoulders.

It is imperative in such scenarios that effective means are provided for transitioning back to the overall shared task [7, 10]. Each synced device will also act as a controller, to allow subgroup work to be mirrored to the shared screen. A central, "super" controller was also proposed; this should be particularly useful for teachers/orchestrators, to maintain an overview of students' classroom activity. Participants saw additional benefits in this, for monitoring subgroup work in order to minimise distraction, to draw attention to a specific solution [11] or, importantly, to recognise where a group requires extra support.

The next stage in our work is to investigate, further, options for achieving this in both software and hardware, to translate the updated requirements and to redesign into a more usable, more effective version of the working prototype. We envisage that this set-up will ensure, also, seamless transition from the video-making activity to the sharing phase, removing the current separation of these steps in the learning process. We will investigate, further, how to enact different learning tasks that support tighter integration between the activities around the shared workspace displays and more traditional classroom activity. This is to ensure that the interplay of the multiple, coupled devices still maintains collaboration during the closely shared task of storyboarding and the more distributed activity in video composition and review, so that the new scaffolds truly augment reflective learning and lead to deep, conceptual understanding of TCs.

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Chapter 24
Students' Learning Environments for Distance International Collaboration

Terje Väljataga

Abstract The paper reports a small-scale study of the bigger research within the context of CoCreat project. With the advent of Web-based tools and services and increasing consumerisation of personal devices, students encounter seamless computing experiences anywhere and any time, thus taking control over knowledge artefacts and environmental conditions. This paper demonstrates an attempt to reconsider the theoretical assumptions underpinning our contemporary understanding and approaches of learning and teaching by implementing trialogical learning elements into course design. The study showed that the pre-selected, obligatory environment for students is nowadays a questionable approach, as many students prefer to build their own landscape of tools and services according to their needs and purposes.

Keywords Trialogical learning · Course design · Learning environments · Higher education · Distance learning

24.1 Introduction

Life and work is increasingly moving towards a digital world requiring people to acquire knowledge and skill base to deal with digital information and environments. Ever-growing digitisation changes the nature of jobs and work tasks blurring the cultural, economical and country boarders. More and more tasks already are and certainly will be done from distance mediated by various social and open technologies. The rapid development of new technology forms qualitatively new possibilities for distributed interaction and collaboration creating opportunities for users to interact, communicate, share, create and modify conceptual artefacts. It is

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not about only watching videos or listening podcasts, but rather creating them themselves and learning through that creation and modification process individually or in groups.

With the advent of social and open technologies, individuals can interact more frequently and openly with considerable degrees of freedom and control, loosing the boundaries between roles (e.g. learners and teachers), between physical and digital spaces, and between formal and informal learning contexts. The opportunities to interact and change ownership and control over knowledge artefacts and environmental conditions allow individuals and systems to be in constant change, creative and co-evolve. This increasingly challenges traditional values, beliefs and practices of education. In particular, it creates pressure to course designs that would allow deliberately create new knowledge and smart environments and open up new ways of learning. The following chapters present one substudy of the bigger research within the context of CoCreat project. The purpose of the study is to demonstrate within a particular course design students' attempt to replace pre-defined learning environments with their own choices of Web-based tools and services.

24.2 Trialogical Learning Metaphor

We build our conceptual framework for the design of learning experiences on a knowledge building [1] and trialogical learning metaphor [2]. Knowledge building and creation stress the importance of idea (conceptual artefact) advancement, expansion and improvement; and the ability of humans to develop cultural or conceptual artefacts. According to Paavola and Hakkarainen [2], knowledge building [1, 3] "can also be interpreted as a form of a trialogical process" (p. 5).

The concept *students as creators and producers* is not entirely a new concept because handicraft as a form of learning has a far reaching history and tradition. However, digitisation has brought along a different type of creation and production by transforming existing practices, thus allowing students to express themselves in different (re-)presentation modes. Knowledge creation metaphor is interpreted as an umbrella term or a meta-theoretical conception [3] to understand "how people collaboratively create and develop novel things with the support of technology" (p. 2) [4]. Thus, the emphasis is on collaboration and interaction through shared objects in (partially) technologically mediated settings to "develop something new collaboratively, not repeating existing knowledge" [3, p. 3]. The objects can be concrete knowledge artefacts, ideas, models, representations, etc. The activities are supported by appropriate technologies depending on what affordances are needed. Paavola and Hakkarainen [2] state that in trialogues, the central aim is not to enhance dialogues, but the common ground is provided by jointly constructing external representations, practices and artefacts. Hakkarainen and Paavola [2] have proposed six, interrelated principal features characterising trialogical learning, which form the basis for the design principles of learning experiences:

1. Organising collective learning activities around shared "objects" (artefacts, practices);
2. Supporting interaction between personal and social levels, and eliciting individual and collective agency;
3. Fostering long-term processes of knowledge advancement;
4. Emphasising development through transformation and reflection between various forms of knowledge and practices;
5. Cross-fertilisation of various knowledge practices across communities and institutions; and
6. Providing flexible tool mediation.

The aforementioned design principles were also taken as a basis for our course design.

24.3 Course Design and Context

The CoCreat project (http://www.cocreat.eu/) supported by the European Commission under the LifeLong Learning programme (http://eacea.ec.europa.eu/) focused on researching the potential for new learning practices in digital, networked environments. The general aim of the research project was to find out how to enhance creative collaboration in the midst of digital transformation.

Within the context of the CoCreat project, a joint international course was developed. The course design followed the ideas of collaborative and problem-based learning, knowledge building, social constructivism and trialogical learning. The aim of the course was to familiarise students with the key concepts, competing theories and approaches of technology-enhanced learning (TEL). The learning goals of the joint course included acquiring the following competences:

- Implementing theoretical knowledge to practical problem-solving (collaboration with international partners of different expertise);
- Working on a conceptual artefact from distance by writing (academic text) collaboratively and creating an independent and legible section to the electronic publication, based on data collected; and
- Designing a virtual environment for supporting international distance collaboration and knowledge building.

The joint course involved students taking local courses: "New Interactive Environments" at the Tallinn University, "Learning Theory and Pedagogical Use of Technology" at the University of Oulu and "Cooperation Technology" at the Norwegian University of Science and Technology. Students (around 80) from all three countries had local activities, developing a specific expertise in order to bring it into the collaborative task. During the joint course, larger international groups were formed (Fig. 24.1). Participating students were divided into seven groups, and each group had members from all three countries. All the joint course activities were conducted distantly over the period of 1.5 months.

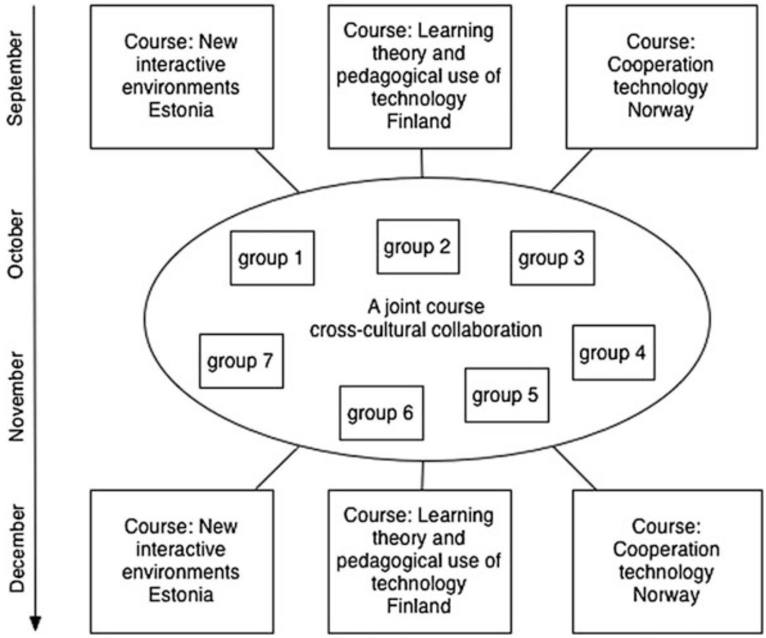

Fig. 24.1 Course design

The collaborative task during the joint course was to create a multimedia book. Each of the book chapters was entitled by a technology-enhanced learning-related challenge designed by CoCreat partners. The groups were expected to base the contents of their chapter on a given scenario that represented real-life challenges of supporting learning with technology. They were instructed to collect data in the field, capturing the real-life practice that would be the basis for their chapter. They were also encouraged to use any creative ways to construct their book chapter and enrich it with different ways and modes of presenting ideas and knowledge. Each international group was tutored by one teacher. The students also worked on peer reviews, providing feedback on other group's draft chapters based on a suggested framework. The collaborative phase of the course ended with the students' presentations of the designed chapters.

The course design emphasised on various digital, networked technologies to create an appropriate "virtual environment" for international students working on a shared artefact. Purot wiki technology was offered for the construction of book chapters as well as for asynchronous discussions and peer-reviewing. It also provided the basic information about the course. Adobe Connect was offered for synchronous discussions. Prezi was offered for creating final presentations. This pre-selected list of tools and services could be seen as a starting set of technology, as the students were encouraged to design and transform their environments in a way they deemed fit for creative collaboration.

24.4 Research Design and Data Collection

The joint international course and its design allowed researchers to observe and explore a number of interesting phenomena in cross-cultural distance collaboration. The paper presents some aspects from the bigger, more comprehensive research project. The main questions framing the data analysis for the research presented in this paper were the following:

1. How did students interact and design their digital learning environments for supporting (or constraining) creative distance collaboration?
2. What were the challenges and limitations in their environments and international collaboration?

The data in the study were collected from several sources and were combined:

- Digital traces of groups Web-based tools and services;
- Interviews with volunteered students from every group; and
- Facebook group conversations of two groups.

Due to our research purpose, the interviews were structured and focused on the following aspects in creative international collaboration:

- Digital learning ecosystems for group collaboration—what, when and why in terms of technology was used, and how the landscape of various tools and services was incorporated into the groups' digital learning ecosystems;
- Problems and challenges in international distance group work—what made the group work challenging and what kind of difficulties the group experienced.

24.5 Digital Learning Environments

Rich and detailed interview data allowed to draw up every group's digital learning environment (in Fig. 24.2, grey boxes represent pre-selected tools, while white boxes represent tools chosen by students) and its evolution. It is obvious that the set of tools and services (Purot wiki for working on an artefact; Adobe Connect for regulating group work; Prezi for final online presentation of the designed artefact) provided by the tutors was not enough for successful creative collaboration. All the groups encountered some problems in the beginning and realised that their landscape of tools and services need to be complemented with or replaced by additional technology in order to get going.

Figure 24.2 shows some similarities in terms of chosen additional tools and services. As Facebook has gained a lot of popularity and quite many people have created accounts there, it is not surprising that all the groups except two decided to create a Facebook group.

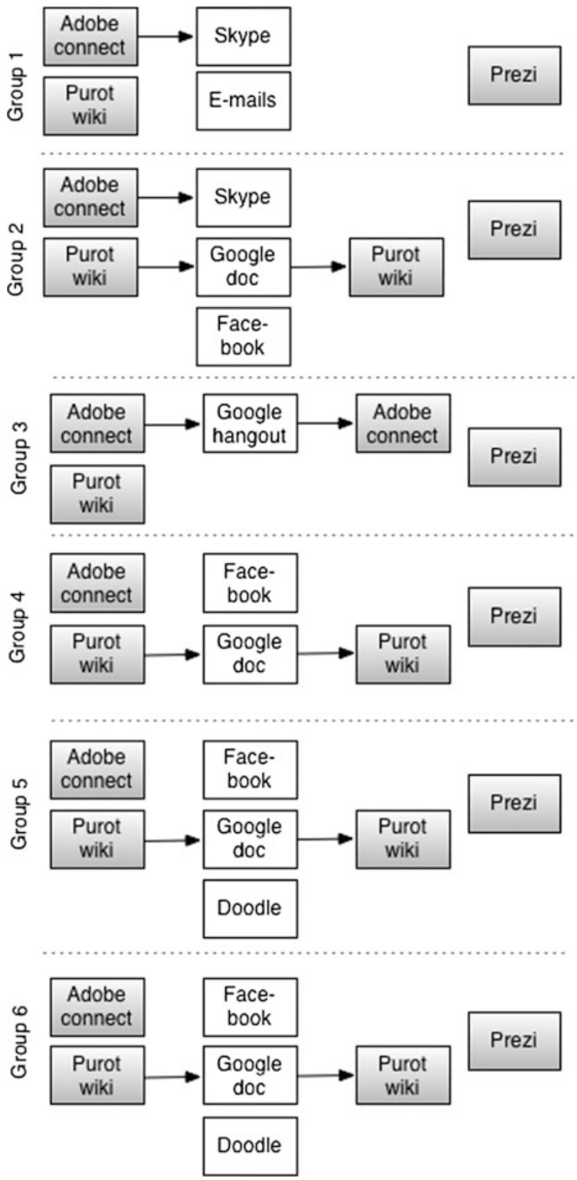

Fig. 24.2 Groups' landscapes of Web-based tools and services

The reason was triggered by the fact that there was no proper communication tool provided. Although Purot wiki had an option to comment and chat in addition to Adobe Connect for synchronous meetings, however, it did not fulfil the requirements and expectations of the groups.

The members of these groups claimed that deciding to use Facebook "was a sort of unvoiced…this decision we made together" (group 7 member). Also, group 6 admitted that "it was maybe the quickest thing and the most efficient thing that the international group has done...it was very impressive how fast we actually get this Facebook group together". The groups considered Facebook as a ready-to-hand tool to simply accomplish a task and to allow everybody to see what is going on and when is the meeting times or just for rapid communication. In addition to its popularity and familiarity among students, the other reason to start using Facebook is related to additional information it provides about its members. For instance, using Facebook the group 7 acknowledged that "…of course it kind of created a better bound for the individuals, where they can see each other, know about each other". It helps to complement the missing "real touch" of the group members and provides more synchronous activities. The group 6 admitted that "… we achieved to have discussions on various subjects I would say. So we opened various threats that were related". Using Facebook for international group work, however, it also had some minor problems. For instance, the group 6 member said that "I had the feeling also that obviously only those discussion that were moving to the top of the page were actually seen by everybody, because people would just have maybe have a short look at the group and then they would like ok this was the last part of the discussion".

Another similar line, which runs through the groups' learning environments, is related to working on a content and an artefact. Purot wiki actually has a number of necessary features for collaborative writing; however, the same 4 groups voted to make use of Google documents as an alternative to Purot wiki because of its limitations. The reasons for leaving Purot wiki were, for example, "you could not see what other people were doing in real time" (group 7) or "Purot wiki is not the best from the usability viewpoint if you want to modify documents by several students" (group 5).

Also, group 6 acknowledged that "there was a certain misunderstanding all the time…how do we access that and how does it work, so there was a bit of insecurity regarding this environment". Thus, the students considered Google documents' affordances more suitable for the given task. "You can write down comments at the same time is the best in a situation where you want to talk at the same time and you have to produce some text" (group 5). "With the Google Documents, you can see what everyone has done. Just like you are working on one document all together. It was an easy way than trying to always meet" (group 4). However, as Purot wiki was a pre-defined tool for all the groups, in the end the content from Google documents was transferred to Purot wiki, where it finally formed a comprehensive book with various chapters produced by every international group.

Many technical problems occurred also while using Adobe Connect for synchronous group meetings. For example, group 6 found Adobe Connect really helpful as long as it worked. "It turned out that only Finnish students could use the audio feature of that service and the others had to type all the time. …the ones who had audio were maybe kind of dominating the discussion". Nevertheless, the group decided to make regular use of that and mainly use the typing feature of that tool because it still enabled to see each other to a certain degree or see each other typing in a real setting. At the same time, group 7 was not so happy about the anonymity of that service "…that it can only be used by one person… and we were just names in Adobe Connect. We were discussing with some sort of anonymity". It is obvious that the affordances of that tool allowed much more than these particular groups actually managed to execute. In general, all the groups struggled with Adobe Connect as it turned out to be technically a bit unstable carrying at the same time some usability issues. Group 1 decided to try out Google Hangouts as an alternative to Adobe Connect, but it did not work out for that group as some group members had not used it before and it was not very intuitive for them. Finally, they fell back to Adobe Connect. As the group members of group 4 did not have microphones, they collaboratively decided to bring in Skype into their digital learning ecosystem. They claimed that "the whole atmosphere did not seem to work for such a big group" while using Adobe Connect and Skype promised to be a more convenient option, even if meetings were done with text chats. The same problem emerged for group 5. One of the members said that "…I originally thought that using Skype, we could actually talk to each other, but then people either did not have microphones or were in places where they could not use microphones. Well, we were still doing Instant messaging, but on Skype it is a lot bigger…And also Skype is easier to keep the whole conversation there and to be able to export it, so that the other people in the group could see the conversation that we had". Prezi as a presentation tool was accepted by most of the groups as one of the requirements from the course tutors despite of some technical problems they sometimes encountered. Group 6 member said "you didn't really have, or really truly collaborative in a sense that, you can't just go back, so you just always have to accept what the other one does".

It is interesting to note that some group organised local "mini groups" and started to make use of their own tools. For instance, in one group local students created a Google document for collecting ideas, carrying out brainstorming and producing a presentable product for other international group members. In addition, a Dropbox folder was created for gathering articles and documents related to their specific task. The interview data also demonstrate that as soon as there was an option to have face-to-face meetings, this option was very often and sometimes even regularly used among local students to discuss about group work issues.

24.6 Problems and Challenges

Working from distance on a shared artefact can be challenging and bring along a number of problems on a social, cultural, knowledge or technological level. The interview data demonstrate that the challenges were not so much related to technological issues and working from distance, but rather motivational, personal factors, limited time and not finding a common ground among group members constrained the smooth progress of the group work.

Only group 6 blamed technology (Adobe Connect) as a major challenge, which was either not working properly or some group members did not know how to use some applications. One of the members claimed that "I think it is difficult to be creative together also when there is a certain distance, I mean this distance doesn't have to be, it can be overcome by, for example, sharing Adobe Connect I would say, but as that didn't work that well technically I think there was still always a bit of distance". A more serious challenge for the groups was to manage time among the group members. Group 7 claimed this to be the only difficulty in their group work. One of the members said that "The only difficulty I remember is being so many people it was very hard to find a common time to work as a single group. We tried to solve it by dividing the group to two smaller subgroups, but it did not quite worked out correctly". Different time zones, personal, study and work life turned out to be the most significant problem during the whole period of the group work. Quite likely, the time issue was also influencing students' motivation to work on the shared artefact. For instance, group 6 and group 3 realised that they lacked information about the importance of the joint course for all the group members, which in turn made some of them think that the course does not play an important role in the overall grading. They learned that it is essential to establish group feeling before really get going with the task. In addition to group 1, group 4 also complained that "the challenge was not being able to connect, it was about people just not connecting". Even dividing tasks among themselves and indicated concrete names for every task did not solve the problem, however, using many communication channels (wiki environment with tasks and names; extra e-mails, etc.) brought some mitigation or in some cases the whole group required major re-organisation because of the disappeared group member. To conclude, most of the groups were able to design and create functioning environments according to their needs and purposes.

24.7 Conclusions

With the advent of Web-based tools and services and increasing consumerisation of personal devices, students encounter seamless computing experiences anywhere and any time. Thus, it becomes possible to collaborate, communicate and connect to ideas and artefacts in entirely new ways through authoring, remixing and co-creating digital, networked artefacts of various kinds and of different representational qualities. This constant interaction, openness and changes of ownership allow taking control over knowledge artefacts and environmental conditions. This paper demonstrated an attempt to reconsider the theoretical assumptions underpinning our contemporary understanding and approaches of learning and teaching by implementing trialogical learning elements. The study showed that pre-selected, obligatory tools and services for students are nowadays a questionable approach, as many students have their own preferences in terms of mediating technology, usage skills and technological opportunities. Our small-scale study showed clearly that most of the teacher chosen and controlled Web-based tools and services were replaced and students built their own smart landscape of tools and services according to their needs and purposes.

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Chapter 25
The Impact of Assigned Roles and Cross-Age Peer Tutors on Knowledge Elaboration, Knowledge Convergence, and Group Performance in Synchronous Online Learning Environment

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Abstract In this chapter, the impact of assigned roles and cross-age peer tutors on knowledge elaboration, knowledge convergence, and learning performance in synchronous online learning environment are investigated. Four fundamental roles were selected: information searcher, explainer, coordinator, and summarizer. The graduate students were designated as cross-age peer tutors, and they were randomly assigned to each group. The knowledge map analytical approach was adopted to analyze and calculate the level of knowledge elaboration and knowledge convergence. The results indicated that there were significant differences in the level of knowledge elaboration and knowledge convergence between the assigned roles groups and group neither roles nor tutors. The significant differences between the group with tutors and the group neither roles nor tutors were also found in the level of knowledge elaboration and knowledge convergence. However, there was no significant difference in group performance among these three conditions. The implications for educators and practitioners as well as future directions are discussed in detail.

Keywords Roles · Cross-age peer tutors · Knowledge elaboration · Knowledge convergence · Group performance

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25.1 Introduction

Synchronous online learning has attracted much attention in recent years and has been widely used in the field of education to promote effective and efficient learning. Previous studies revealed that online discussions were helpful in achieving higher order learning objectives [1]. Furthermore, synchronous online discussions allow learners to interact with each other real-time and clarify ideas immediately [2].

However, online discussion will be less effective if only dividing students into different groups [3]. Therefore, several instructional approaches in online discussion were explored so as to promote and facilitate collaborative learning. For example, providing the specific structure by means of scripts proposed by Dillenbourg [4] was an effective approach which can structure the collaborative process and elicit the productive interaction. This study focuses on two structuring approaches: one is to assign different roles to group members and another is to assign a cross-age peer tutor to each group. In addition, knowledge construction is the central issue in collaborative learning. We believe that knowledge elaboration and knowledge convergence are two aspects of knowledge construction. The following section will provide the related studies on role assignment, peer tutor, knowledge elaboration, and knowledge convergence.

25.2 Literature Review

25.2.1 Roles in Online Learning Environment

Roles can be defined as given functions or responsibilities that can facilitate individual behavior and regulate collaboration [5]. Strijbos et al. [6] reported that the groups with assigned roles have a higher degree of perceived group efficiency than no-role groups. De Wever et al. [7] also found that roles can stimulate social knowledge construction and group efficiency. Roles have potential positive impact on eliciting constructive feedback from peers in online learning environment [8]. However, little is known about the impact of assigned roles on knowledge elaboration, knowledge convergence, and group performance.

There are many roles, such as starter, theoretician, coordinator, explainer, searcher, and summarizer. In this study, information searcher, explainer, coordinator, and summarizer were selected. The inclusion of the information searcher was based on the previous research that reported a need for seeking information to gain a better understanding of subject matter [9]. The explainer was included on the basis of findings indicating that providing explanations can produce increased learning performance [10]. The coordinator was selected because collaborative learning is a coordinated activity with meaning negotiation that aims to construct and maintain a shared understanding [11]. The summarizer was taken into account because summaries result in significantly higher levels of knowledge construction [12]. In a word, the information searcher, explainer, coordinator, and summarizer are equally important in CSCL. Therefore, they were selected and introduced in the present study.

25.2.2 Peer Tutors in Online Learning Environment

Peer tutoring is built on the theory of zone of proximal development proposed by Vygotsky [13] who believed that the potential development level can be determined through problem solving with the aid of more capable peers. Thus, the distance between the actual developmental level and the potential development level can be decreased by peer tutor's scaffold. Also, tutee is more easily to be embedded in the learning network facilitated by peer tutors [14].

Cross-age peer tutoring means that older or more able learners tutor younger or less able learners [15]. It is widely acknowledged that synchronous online discussion requires real-time interaction and immediate responses. Therefore, it is helpful and useful to introduce a cross-age peer tutor in synchronous discussion groups, since peer tutors can flexibly regulate the tutee's behavior as well as their own based on the ongoing collaboration processes [12]. Previous studies also revealed that students supported by cross-age peer tutors reached high level of knowledge construction [12]. However, the impact of cross-age peer tutors on knowledge elaboration and knowledge convergence in synchronous online learning context has not been systematically examined.

25.2.3 Knowledge Elaboration and Knowledge Convergence

Knowledge elaboration means to restructure and integrate new information with the previous knowledge [16]. Based on the previous studies, the fundamental elaborative elements included as follows: organizing concepts, sequencing ideas, integrating novel information, integrating prior knowledge, restructuring information, and constructing new knowledge [17]. Therefore, the level of knowledge elaboration was measured either according to the basic elaborative elements [17] or based on the other coding schemes [18]. In addition, questionnaire, think-aloud protocols, or assigning values of −1, 0, and 1 were adopted to evaluate the level of knowledge elaboration. However, these methods are very subjective and ambiguous when analyzing the processes of knowledge elaboration [19]. Also, the process of constructing knowledge was ignored to a large extent [20].

Knowledge convergence refers to how common knowledge is constructed after collaboration [21]. Previous studies adopted different kinds of methods to assess the level of knowledge convergence. For example, Jeong and Chi [22] calculated the increase in common knowledge based on pretest and post-test. Clariana et al. [23] adopted the degree centrality of a graph to assess knowledge convergence. It is obvious that these measurements cannot help to get a better understanding of the knowledge convergence process at the group level. This study adopted the knowledge map analytical approach to measure the level of knowledge convergence. The following section will describe the method in detail.

This study aims to determine the impact of assigned roles and cross-age peer tutors on group performance, knowledge elaboration, and knowledge convergence in synchronous online learning environment. The research questions are addressed as follows:

1. Are there any differences in group performance among the assigned roles groups, groups with tutors, and groups neither roles nor tutors?
2. Are there any differences in knowledge elaboration among the assigned roles groups, groups with tutor, and groups neither roles nor tutors?
3. Are there any differences in knowledge convergence among the assigned roles groups, groups with tutors, and groups neither roles nor tutors?

25.3 Methodology

25.3.1 Participants

A total of 192 college students voluntarily participated in this study. These students were majoring in Education or Psychology Science. They were randomly divided into 48 groups of four. 16 groups were randomly assigned different roles, 16 groups were assigned a cross-age tutor for each group, and the left 16 groups had neither roles nor the tutor.

25.3.2 Collaborative Learning Task

The collaborative learning tasks focused on the strategies of problem solving. The tasks were identical for all of 48 groups. Participants needed to collaboratively complete the following tasks:

- How do you solve the following problem by existing strategies?
- One evening, four persons have to cross a suspension bridge that can only hold two persons at the same time. Also, only one electric flashlight that can last for 17 min is available. The first person needs 1 min to cross the bridge, the second person needs 2 min, the third person needs 5 min, and the fourth one needs ten minutes. In this case, how can these four persons across the bridge?
- Can you illustrate how to solve ill-structured problems?
- Can you explain the differences between experts and novices? Do you think how to become an expert in your research area?

25.3.3 Procedure

The experimental procedure included pretest, collaborative learning, and post-test. First, the pretest that took 20 min was administered to all of participants. Then, all of groups conducted synchronous online discussion via MSN for 2 h in different laboratories at different timeslots. 192 participants were randomly assigned to one of three conditions: assigned roles groups (experiment group 1), groups with tutors (experiment group 2), and groups neither roles nor tutor. The specific guidelines were instructed to assigned roles groups and groups with tutors before the experiment. The responsibilities of each role and peer tutors are shown in Tables 25.1 and 25.2, respectively. Finally, the post-test with the same test items was administered to all participants. Both the items of pretest and post-test are subjective test items closely related to collaborative learning tasks.

25.3.4 Data Analysis Method

The data collected via MSN were logged and analyzed by our tool. This tool is developed based on knowledge map analytical approach. There are three steps

Table 25.1 The definitions of different functional roles

Role	The definitions of the role
Information searcher	Search for external information and resources that are closely related to collaborative learning tasks
Explainer	Integrate the new information with prior knowledge, provide elaborate explanations as much as possible, and clarify any points that are still unclear
Coordinator	Monitor and coordinate the whole collaborative learning process, encourage group members to be engaged in collaborative learning, solve the conflicts, and ask critical questions
Summarizer	Post-interim summaries during the discussion, summarize the main ideas and solutions, form a final summary and conclusion after collaboration

Table 25.2 The guidelines for peer tutors

Responsibilities	Descriptions
Motivation	Welcome and encourage each group member to participate in the collaborative learning
Information exchange	Ensure that the discussions focus on the collaborative learning task and explore the problems deeply
Knowledge construction	Elaborate information, negotiate meaning, and building common understanding
Critical thinking	Promote critical thinking by scaffolding tutees to make comments on others' opinions

when we analyze the data via our tool: First, drawing a knowledge map according to the collaborative learning tasks. Second, coding information generated during the collaboration processes and mapped onto the knowledge map. Finally, calculating the level of knowledge elaboration and knowledge convergence via the tool. For more details, please refer to Zheng et al. [24].

25.4 Results

25.4.1 RQ1: Are There Any Differences in Group Performance Among the Assigned Roles Groups, Groups with Tutors, and Groups Neither Roles nor Tutors?

The pretest was administered to evaluate the differences in prior knowledge among the three groups before the experiment. The descriptive statistics of the pretest are presented in Table 25.3. The ANOVA results indicated that there was no significant difference in pretest between the three groups ($F = 2.59$, $p = 0.09$). Therefore, the prior knowledge of the three groups could be perceived as equivalent.

The ANCOVA results of group performance are shown in Table 25.4. The means and standard deviations of group performance were 13.64 and 8.18 for experiment group 1, 13.61 and 4.73 for experiment group 2, and 12.97 and 7.06 for control group. It was found that although both the experimental groups had higher mean scores than the control group, there was no significant difference among experiment group 1, experiment group 2, and control group ($F = 0.070$, $p > 0.05$). This finding revealed that the three kinds of groups experienced equivalent levels of group performance. This implied that assigned roles and peer tutors did not have significant impacts on group performance.

Table 25.3 Pretest results of three groups

Group	N	Mean	SD
Experiment group 1	16	18.14	3.07
Experiment group 2	16	15.56	3.65
Control group	16	16.16	3.28

Table 25.4 ANCOVA results of group performance for the experiment groups and the control group

Group	Group performance			
	Mean	SD	**F**	*p*
Experiment group 1	13.64	8.18	0.070	0.932
Experiment group 2	13.61	4.73		
Control group	12.97	7.06		

25.4.2 RQ2: Are There Any Differences in Knowledge Elaboration Among the Assigned Roles Groups, Groups with Tutor, and Groups Neither Roles nor Tutors?

Table 25.5 shows the ANOVA results of knowledge elaboration for the experimental groups and control group. The results revealed that there was a significant difference between the two experiment groups and the control group ($F = 4.041$, $p < 0.05$). The two experiment groups outperformed the control group in terms of knowledge elaboration. In other words, the students in both experimental group 1 and experimental group 2 had significantly better knowledge elaboration level than the control group. Therefore, it is concluded that assigned role and scaffold by tutors are more helpful to the students in terms of knowledge elaboration. However, no significant difference was found between the experiment group 1 and the experiment group 2 ($p > 0.05$), showing that the two groups of students had the similar level of knowledge elaboration in collaborative learning activity.

25.4.3 RQ3: Are There Any Differences in Knowledge Convergence Among the Assigned Roles Groups, Groups with Tutors, and Groups Neither Roles nor Tutors?

The results of knowledge convergence for the two experiment groups and control group are demonstrated in Table 25.6. The results indicated that there was a significant difference between the experiment groups and the control group ($F = 3.386$, $p < 0.05$). The participants in the experiment group 1 and the experiment group 2 outperformed the control group. In other words, scaffolding by peer tutors and assigning roles are more useful for learners with regard to knowledge convergence. However, there was no significant difference between the experiment group 1 and the experiment group 2 ($p > 0.05$). This also revealed that these two groups of participants had the equivalent level of knowledge convergence during the collaborative learning process.

Table 25.5 ANOVA results of knowledge elaboration for experiment groups and control group

Group	Knowledge elaboration				Pairwise comparisons
	Mean	SD	**F**	*p*	
Experiment group 1	1049.48	421.61	4.041	0.024	
Experiment group 2	1008.20	568.18			(E1) > (C)
Control group	661.46	196.97			(E2) > (C)

Table 25.6 ANOVA results of knowledge convergence for experiment groups and control group

Group	Knowledge convergence				Pairwise comparisons
	Mean	SD	**F**	*p*	
Experiment group 1	171.13	132.51	3.386	0.043	
Experiment group 2	126.66	127.16			(E1) > (C)
Control group	70.52	47.99			(E2) > (C)

25.5 Discussion

As we know, collaborative learning does not always lead to improved group performance. Only dividing students into different groups does not necessarily produce effective interactions. To promote productivity and performance, there is a need to provide external support and an amount of structure. One specific technique for generating structure is to assign different roles or peer tutor to group members. As a scripting tool, roles can provide the structure to help group members to complete tasks and facilitate interactions [7]. Learners can absorbedly complete tasks and perceive a sense of responsibility with structured roles. In addition, peer tutor had a positive effect on student–student interaction in online learning environment [25]. Furthermore, cross-age peer tutors can facilitate knowledge construction and help learners to focus on learning contents [15].

The present study examined the impact of the two structuring approaches on group performance, knowledge elaboration, and knowledge convergence in online synchronous discussions. One is to assign different roles to the group members, and the other is to assign a cross-age peer tutor to each group. The results revealed that assigning roles and cross-age peer tutors can significantly lead to higher level of knowledge elaboration and knowledge convergence than groups neither roles nor tutors. This finding was in-line with the previous report that both role support and tutor support can enhance the knowledge construction level [12]. However, this is not the case for group performance. In other words, assigning roles and cross-age peer tutors did not affect group performance. The result was consistent with earlier findings that roles had no impact on learning performance [6]. This can be explained that group performance was obtained based on the pretest and post-test. Therefore, the knowledge construction process was ignored in terms of the impact of assigned roles and peer tutors on learning process.

The present study adopted an innovative knowledge map approach to analyze knowledge elaboration and knowledge convergence. This new analysis method is based on a graph theory approach, which highlights to represent the knowledge construction process by the knowledge map. It is quite different from the previous studies which adopted questionnaire or think-aloud protocols to measure the level of knowledge elaboration. It also differs from the previous method that using pretest and post-test to measure the level of knowledge convergence [22]. The knowledge map approach aims to gain insights into the process of knowledge convergence and represent them through the knowledge map.

There are several limitations in the present study. First, the detailed analysis of the quality of the role contributions was not taken into account in this study, for example, the efficiency of coordinators, the correctness of explanations, and accuracy of the summaries. Therefore, the contributions of each role should be thoroughly analyzed so as to gain insight into differences among them. Second, all tutors have not been trained before the experiment. Therefore, sometimes tutors cannot perform the responsibilities well. In the future study, tutor training will be conducted in order to achieve the productive collaborative learning. Finally, the impacts of role assignment and peer tutor on motivation and engagement have not been investigated in the present study. The future study will examine the effects of role assignment and peer tutor on affective and behavioral parameters.

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Chapter 26
Toward Non-intrusive Assessment in Dialogue-Based Intelligent Tutoring Systems

Vasile Rus and Dan Stefanescu

Abstract This paper describes a study whose goal was to assess students' prior knowledge level with respect to a target domain based solely on characteristics of the natural language interaction between students and a state-of-the-art conversational ITS. We report results on data collected from two conversational ITSs: a micro-adaptive-only ITS and a fully adaptive (micro- and macro-adaptive) ITS. Our models rely on both dialogue and session interaction features including time-on-task, student-generated content features (e.g., vocabulary size or domain-specific concept use), and pedagogy-related features (e.g., level of scaffolding measured as number of hints). Linear regression models were explored based on these features in order to predict students' knowledge level, as measured with a multiple-choice pre-test, and yielded in the best cases an $r = 0.949$ and adjusted r-square = 0.878.

Keywords Intelligent tutoring systems · Knowledge assessment · Tutorial dialogues

26.1 Introduction

Assessment is a key element in education in general and in intelligent tutoring systems (ITSs) in particular because fully adaptive tutoring presupposes accurate assessment [1, 15]. Indeed, a necessary step toward instruction adaptation is assessing students' knowledge state such that appropriate instructional tasks (macro-adaptation) are selected and appropriate scaffolding is offered while students are working on a task (micro-adaptation). We focus in this paper on assessing students' prior knowledge in dialogue-based ITSs based on characteristics of the tutorial dialogue interaction between the students and the intelligent tutoring system DeepTutor ([8]; www.deeptutor.org).

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When students start interacting with an ITS, their prior knowledge with respect to the target domain is typically assessed using a multiple-choice pre-test although other forms of assessment such as open answer problem solving are sometimes used. The pre-test serves two purposes: enabling macro-adaptation in ITSs, i.e., the selection of appropriate instructional tasks for a student based on student's knowledge state before the tutoring session and, when paired with a post-test, establishing a baseline from which student progress is gauged, e.g. by computing learning gains (post- minus pre-test score). This widely used pre-test/post-test experimental framework is often necessary in order to infer whether the treatment was effective relative to the control.

While the role of a pre-test is important for assessing students' prior knowledge, there are several challenges with having a pre-test. First, a pre-test (as well as the paired post-test) takes up a non-trivial amount of time. This is particularly true for experiments consisting of only one session in which case the pre-test and post-test may take up to half the time of the full experiment. For instance, a 2-h experiment could be broken down into three parts: 30 min for pre-test, 1 h of actual interaction with an ITS, and 30 min for post-test. Altogether, in this particular case, the pre-test and post-test take 1 h, which is half the time of the whole experiment. More worrying is the fact that in such experiments, the pre-test may have a tiring effect on students. By the time students reach the post-test, many of them will be so tired that they will underperform even if they learned something during the actual training, thus jeopardizing the whole experiment. For instance, in one of our experiments, about 30 % of the subjects simply randomly picked one of the choices for the multiple-choice questions in the post-test without even reading the question. We observed this by looking at the time they took to pick their choice after they were shown the question on screen. About a third of the students took on average less than 5 s per question which is not even enough to read the text of the question. By comparison, the same students took on average 36 s to respond to similar questions in the pre-test. By eliminating the pre-test in the above illustrative experiment, we can reduce the overall experimental time to 1 h and 30 min, thus reducing tiring effects. By eliminating both the pre-test and post-test, we can further reduce the total experimental time.

Additionally, many times there is a disconnect between the pre- and post-test questions and the actual learning tasks and process. To overcome this challenge, [11] argue for a shift toward emphasizing performance-based assessment which is about evaluating students' skills and knowledge while applying them in authentic contexts. For instance, reading instructions in a role-playing game allows assessing students reading comprehension skills [11]. Using explicit tests in such contexts would interfere with the main task and are therefore not recommended. They advocate for the use of stealth assessment while students engage in a particular activity. Like in stealth assessment, we advocate here for non-intrusive assessment during problem solving in dialogue-based ITSs.

Our goal in this work was to investigate to what degree we could automatically infer students' knowledge level directly from their performance while engaging in problem solving. Eliminating the need for learners to go through a standard pre-test and post-test will save time for more training, eliminate tiring effects and testing anxieties, and ultimately provide a more accurate picture of students' capabilities as the assessment is conducted in context, i.e., while they engage in problem solving. In particular, we investigate how well we can predict students' prior knowledge, as measured by a standard multiple-choice pre-test, based on characteristics of the tutorial dialogue interaction with the hope that if the predictions are good enough, we can do without the pre-test. We are also interested in finding out the minimum tutorial dialogue interaction that would yield an accurate estimate of students' prior knowledge.

We would like to emphasize that we are not arguing for a complete elimination of multiple-choice assessments, which have their own advantages. Rather, we propose to investigate to what extent we can measure students' knowledge level from interaction characteristics such that, when necessary, we can employ this kind of non-intrusive assessment.

We conducted our research on dialogue data collected from an experiment with high school students using the state-of-the-art conversational computer tutor DeepTutor [8]. As mentioned, our goal was to find interaction features that would be good predictors of students' pre-test scores and to create prediction models that would be as useful as the multiple-choice tests in measuring students' prior knowledge. The best model can predict students' prior knowledge, as measured by a summative pre-test, with $r = 0.878$ and adjusted r-square = 0.693. We also determined the minimum dialogue length which is necessary to be able to make the best predictions.

The remainder of the paper is organized as follows: Sect. 26.2 briefly discusses related work, and Sect. 26.3 describes the approach, while the data are presented in Sect. 26.4. Section 26.5 offers details about the various models and results. The paper ends with a section on conclusions and further work.

26.2 Related Work

The most directly relevant previous work to ours is by Lintean et al. [5] who studied the problem of inferring students' prior knowledge based on prior knowledge activation (PKA) paragraphs elicited from students. PKAs were generated by students as part of a meta-cognitive training program. Lintean and colleagues employed a myriad of methods to predict students' prior knowledge including comparing students' PKA paragraphs to expert-generated paragraph or to a taxonomy of concepts related to the target domain, which in their case was biology. Students' prior knowledge level or mental model was modeled as a set of three categories: low mental model, medium mental model, and high mental model. There are significant differences between our work and theirs. First, we deal with dialogues as opposed to explicitly elicited prior knowledge paragraphs. Second, we do not have access to a taxonomy of concepts against which we can compare students' contributions. Third, we model students' prior knowledge using the score obtained from the multiple-choice pre-test.

Predicting students' learning and satisfaction is another area of research directly relevant to ours. Among these, we mention the work of Forbes-Riley and Litman [4] who used three types of features to predict learning and user satisfaction: system-specific, tutoring-specific, and user-affect-related. They use the whole training session as unit of analysis, which is different from our own analysis because we use instructional task, i.e., a physics problem in our case, as the unit of analysis. Our unit of analysis serves better our purpose of finding out the minimum number of leading instructional tasks in a session to accurately assess students' knowledge level. Furthermore, their work was in the context of a spoken dialogue system, while in our case we focus on a chat-based/typed-text-based conversational ITS. Another difference between our work and theirs is their focusing on user satisfaction and learning, while we focus on identifying students' knowledge level.

Williams and D'Mello [14] worked on predicting the quality of student answers (as error-ridden, vague, partially correct or correct) to human tutor questions, based on dictionary-based dialogue features previously shown to be good detectors of cognitive processes (cf. Williams and D'Mello [14]). To extract these features, they used LIWC [6], a text analysis software program that calculates the degree to which people use various categories of words across a wide array of text genres. They reported that pronouns (e.g., I, they, those) and discrepant terms (e.g., should, could, would) are good predictors of the conceptual quality of student responses.

Yoo and Kim [16] worked on predicting the project performance of students and student groups based on stepwise regression analysis with dialogue features in online Q&A discussions. To extract dialogue features, they made use of LIWC and speech acts. For their problem, they found that the degree of information provided by students and how early they start to discuss before the deadline are two important factors explaining project grades. A similar research was conducted by Romero et al. [7] who also included (social) network-related features. Their statistical analysis showed that the best predictors related to students' dialogue are the number of contributions (messages), number of words, and the average score of the messages.

In our work presented here, we use some of the features described by the above researchers, such as session length or dialogue turn length, and other novel qualitative features such as information content.

26.3 The Approach

Our approach to predict students' knowledge level in the context of dialogue-based ITSs relies on the fact that each tutorial dialogue between the system and a student has its own characteristics which are strongly influenced by student's background and the nature of instructional tasks. Indeed, students' knowledge level is reflected in the tutorial dialogue between the system and the student, e.g., as the learner becomes more competent, the level of help from the ITS should drop. The level of help can be quantified as the number of hints, for instance. Furthermore, the dialogue characteristics are also influenced by the nature of the training tasks. If similar tasks (addressing same concepts in similar or related contexts) are used throughout the whole session, one might expect that by the time a student reaches the last problems in the session, he would master them, thus requiring less help at the end of the session. On the other hand, if the problems are increasingly challenging or simply unrelated to each other, then the students will be continuously challenged throughout the whole session; in such a scenario, the number of hints a student receives should not drop throughout a session.

We are exploring the relationship between students' prior knowledge and dialogue features in two different setups with two different task selection strategies, which allows us to explore the impact of different task selection policies on the dialogue characteristics and therefore on our models for predicting students' prior knowledge. Indeed, we work with data collected from training sessions with two versions of an ITS: micro-adaptive-only and fully adaptive (macro- and micro-adaptive). In the micro-adaptive-only condition, students are working on tasks that were so selected to address typical challenges for all students, i.e., following a one-size-fits-all approach. In this micro-adaptive-only condition, students received scaffolding while working on a task (within-task adaptivity) based on their individual performance on that particular task. For instance, if a student articulated a misconception during the solving of a problem, the system would correct it.

In the macro-adaptive condition, students were grouped into four groups corresponding to four knowledge levels (low knowledge, medium-low knowledge, medium-high knowledge, and high knowledge) and appropriate instructional tasks were assigned to each group using an item response theory style analysis [9]. That is, high-knowledge students received more challenging problems appropriate for their level of expertise, while the low-knowledge students received less challenging problems. The consequence of this more adaptive task selection policy will be reflected in the dialogue characteristics as, for instance, the percentage of hints (explained later) is expected to be similar for both high-knowledge and low-knowledge students as the tasks are similarly challenging relative to their level of knowledge. Within a task, the fully adaptive ITS offered identical micro-adaptivity to the micro-adaptive-only ITS. It should be noted that in the micro-adaptive-only case, the problems were selected (two each) from the set of problems used for the four knowledge groups in the fully adaptive condition.

The Features. The proposed approach relies on a set of dialogue features which can be classified into three major categories: time-on-task, generation, and pedagogy. Time-on-task, which reflects how much time students spend on a learning task, correlates positively with learning [12]. Time-on-task is measured in several different ways in our case such as total time (in minutes) or normalized total time (we used the longest dialogue as the normalization factor). We computed several additional time-related features such as average time per turn and winsorized versions of the basic time-related features.

Generation features are about the amount of content/text produced by students. Greater word production has been shown to be related to deeper levels of comprehensions [2, 13]. We mined from our dialogues many generation-related features such as dialogue length, average turn length, vocabulary size, content word vocabulary size (content words: nouns, verbs, adjectives, and adverbs), and target domain vocabulary size, i.e., a measure of how many words from our target, which Physics, students used.

Lastly, we extracted pedagogy-related features such as how much scaffolding a student received (e.g., number of hints) during the training. Scaffolding is well documented to lead to more learning than lecturing or other, less interactive types of instruction such as reading a textbook [13]. Feedback is an important part of scaffolding, and therefore, we also extracted features about the type (positive, neutral, negative) and frequency of feedback [10].

We extracted raw features as well as normalized versions of the features. In some cases, the normalized versions seem to be both more predictive and more interpretable. For instance, the number of hints could vary a lot from simpler/short problems, where the solution is relatively short and requires less scaffolding in general, to more complex problems with longer solutions which require more scaffolding as there are more steps in the solution. A normalized feature such as percentage of hints would allow us to better compare the level of scaffolding in terms of hints across problems of varying complexity or solution length. In our case, we normalized the number of hints by using the maximum number of hints a student may get, which happens when the student responds entirely incorrectly. We can infer the largest number of helpful moves from our dialogue management components a priori.

Due to space constraints, we do not provide the full list of features. We will mention the most important ones throughout the paper as we present various results of our study. For reference, we mined a total of 43 features from 1200 units of dialogue which led to 43 × 1200 = 51,600 measurements. Our unit of dialogue analysis was a single problem in a training session. Because the force-and-motion training session consisted of 8 problems and we collected 150 sessions from 150 students, we ended up with 8 × 150 = 1200 dialogue units.

26.4 The Data

As already stated, we conducted our research on log files from DeepTutor [8], the first ITS based on the framework of Learning Progressions (LPs; [3]). DeepTutor is a conversational ITS based on constructivist theories of learning. DeepTutor encourages students to self-explain solutions to complex science problems and only offers help, in the form of hints, when needed, e.g., when the student is floundering. It is beyond the scope of this paper to present all the details of the system.

An important aspect of the data we use is the fact that it was collected from system–student interactions outside of the laboratory. The data were collected during a multisession, online, after-school experiment in which students interacted with DeepTutor over a period of 5 weeks (one hour of training per week plus pre- and post-tests). The pre-test and post-test were taken over the Web during school

Table 26.1 Statistics of the dialogue corpus

Condition	#Complete Dlg. files	#Student Dlg. turns	#Sentences
Interactive	80	4587	**5102**
Adaptive	70	3604	**4154**
Total	150	8191	9256

hours, under the strict supervision of a teacher. All training sessions were unsupervised as the student chose when and where from to access DeepTutor. This was possible because DeepTutor is a fully online conversational ITS which can be accessed from any device with an Internet connection.

Students were encouraged to finish each training session in one sitting. While many did so, some others have finished the training sessions in multiple sittings, spanning several days in a week. We only included in our analysis here students who finished all sessions (all five sessions) and did so in one sitting. That is, we analyzed dialogues from 150 students, which is the cohort that finished everything (365 students took the pre-test). Each training week, about 225 students accessed the system on average. The participants were randomly assigned to one of two conditions mentioned earlier: micro-adaptive-only (n = 70) and fully adaptive (n = 80). We only analyzed in this paper dialogue corresponding to the first session of training because it was closest to the pre-test. Table 26.1 shows quantitative statistics on these data.

26.5 Experiments and Results

Our goal was to understand how various dialogue units, corresponding to one instructional task in a session, individually and as groups relate to students' prior knowledge as measured by the pre-test, which is deemed as an accurate estimate of students' prior knowledge level. The group analysis would indicate after how much dialogue, corresponding to consecutive training problems, one can accurately infer students' pre-test score.

After acquiring all the features for the subdialogues corresponding to individual problems, our first step was to identify the features whose values best correlate with the pre-test scores. Details of this step are only briefly addressed next due to space reasons. The features with the best correlations were as follows: The time length (ft1), the total number of sentences (fg7), the number of turns (fs1), and the number of hints (fs11) and prompts shown (fs12) have negative correlations with the pre-test scores, while the average word length of a turn (fg2) and the percentage of turns receiving positive feedback (fs7) have positive correlations. These findings confirm similar findings from previous studies [13]. Interestingly enough, the number of sentences students produce seems to be less and less correlated with the pre-test scores as the students advance through the training session.

To predict students' knowledge levels, we generated regression models from subsets of consecutive problems in a training session in order to understand after how many problems the prediction of students' knowledge level is best. The models were generated not only based on all the available features, but also based on subsets of features corresponding to the three major categories of features: time-on-task, generative, and pedagogy/scaffolding. All the models were generated using the backward method in SPSS, a statistical analysis software, so as to be able to find the *r* value corresponding to the highest adjusted *r*-square value and the lowest degrees of freedom (fewest predictors). It is important to note that in the macro-adaptive condition, the models were generated separately for the four groups of students corresponding to the four knowledge levels.

The results in Tables 26.2 and 26.3 indicate that after only four problems, the explained variance is comparable to the best case, which is obtained using the first 6 out of the 8 tasks. Scaffolding-related features as a group seem to do better.

Tables 26.4 and 26.5 present results for dialogues from the fully adaptive condition. Similar to the results obtained from the micro-adaptive-only condition, the scaffolding features as a group do best. Interestingly, in this case, after only two problems, the correlation coefficient r is quite high. In a way, this is a validation that

Table 26.2 *r* (top) and adjusted *r*-square (bottom) values for cumulative subdialogues in the micro-adaptive-only condition and the pre-test

	1	1–2	1–3	1–4	1–5	1–6	1–7	1–8
All	0.735	0.706	0.726	0.819	0.814	**0.878**	0.860	0.871
	0.451	0.426	0.458	0.600	0.589	**0.693**	0.669	0.678
Time	0.462	0.618	0.654	0.692	0.706	0.712	**0.733**	0.709
	0.193	0.358	0.406	0.436	0.465	0.481	**0.507**	0.483
Gen	0.606	0.616	0.668	0.679	0.724	0.739	**0.763**	0.762
	0.265	0.329	0.374	0.408	0.456	0.495	**0.528**	0.520
Scaf	0.593	0.587	0.599	**0.647**	0.603	0.615	0.603	0.607
	0.289	0.310	0.306	**0.343**	0.302	0.308	0.311	0.317

Table 26.3 *r* (top) and adjusted *r*-square (bottom) values for cumulative subdialogues in the micro-adaptive-only condition and the pre-test FM

	1	1–2	1–3	1–4	1–5	1–6	1–7	1–8
All	0.725	0.677	0.713	0.840	0.791	**0.878**	0.857	0.861
	0.449	0.405	0.438	0.611	0.552	**0.693**	0.667	0.681
Time	0.510	0.600	0.613	0.665	0.677	**0.698**	0.690	0.689
	0.260	0.335	0.360	0.404	0.422	0.452	0.448	**0.454**
Gen	0.606	0.578	0.616	0.685	0.698	0.722	**0.750**	0.745
	0.265	0.279	0.338	0.392	0.421	0.459	0.492	**0.497**
Scaf	0.561	0.569	0.573	**0.625**	0.586	0.578	0.576	0.577
	0.259	0.278	0.273	**0.322**	0.249	0.279	0.287	0.288

Table 26.4 *r* (top) and adjusted *r*-square (bottom) values for cumulative subdialogues in the fully adaptive condition and the pre-test

	1	1–2	1–3	1–4	1–5	1–6	1–7	1–8
All	0.820	0.910	**0.949**	0.930	0.922	0.935	0.936	0.924
	0.589	0.764	0.833	0.812	0.788	0.802	**0.839**	0.811
Time	0.566	0.723	0.837	0.847	0.841	0.823	0.882	**0.865**
	0.290	0.509	0.677	0.701	0.684	0.652	0.752	**0.724**
Gen	0.782	0.862	0.904	0.906	0.896	0.850	**0.909**	0.884
	0.530	0.671	0.771	0.791	0.774	0.675	**0.807**	0.749
Scaf	0.709	0.662	**0.838**	0.769	0.754	0.752	0.782	0.804
	0.472	0.394	**0.679**	0.552	0.511	0.508	0.574	0.606

Table 26.5 *r* (top) and adjusted *r*-square (bottom) values for cumulative subdialogues in the fully adaptive condition and the pre-test FM

	1	1–2	1–3	1–4	1–5	1–6	1–7	1–8
All	0.811	0.862	0.865	0.856	**0.896**	0.878	0.889	0.875
	0.562	0.638	0.667	0.639	0.696	0.663	**0.716**	0.633
Time	0.441	0.622	0.739	0.738	0.725	0.689	**0.778**	0.707
	0.158	0.349	0.510	0.510	0.489	0.434	**0.560**	0.452
Gen	0.699	0.808	0.837	0.810	0.792	0.781	**0.849**	0.811
	0.431	0.572	0.631	0.592	0.556	0.544	**0.662**	0.585
Scaf	0.686	0.495	**0.702**	0.663	0.657	0.668	0.705	0.661
	0.446	0.211	**0.444**	0.355	0.357	0.374	0.432	0.394

the problem selection strategy does a good job at selecting most appropriate problems for each of the four knowledge groups. We know that the problems were appropriately selected because the learning gains for students in the macro-adaptive condition were significantly higher than for students in the micro-adaptive-only condition (not reported here).

26.6 Conclusions and Future Work

We explored in this paper models to predict students' prior knowledge based on features characterizing the dialogue-based interaction between a computer-based tutor and a learner. This work was part of our greater goal to move toward non-intrusive assessment methods such that learners could focus on the task, e.g., solving problems or playing a game.

Our results are quite promising with respect to moving toward a world in which learners focus on instructional with no explicit testing. Indeed, our linear regression models based on a number of dialogue features yielded in the best cases an $r = 0.949$

and adjusted r-square = 0.878. Scaffolding features seemed to be the most predictive as a group, as somehow anticipated, followed by content generation features. We plan to further explore the topic of assessing students' prior knowledge from dialogues by investigating affect-related features as well as by using other prediction mechanisms such as classifiers to predicting categorical knowledge levels. Furthermore, we plan to study how similar models can predict post-test scores.

We are aware that students' knowledge levels evolve during training, assuming they learn, and therefore, there are limitations to our methodology. We do plan to explore in the future ways to infer students' knowledge level throughout a session.

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Chapter 27
May I Peer-Review Your Web Design Project?

Veronika Dropčová, Martin Homola and Zuzana Kubincová

Abstract Peer reviews are useful to engage students with their peers' course work, leading to mutual reflection on the topic of interest, and consequently to increased quality of learning. We share our experience with the application of peer reviews on a full-semester project assignment in a Web design course. We describe the methodology that we developed and employed to manage the peer review process and analyze the results in terms of improved learning outcomes.

Keywords Peer review · Course work · Methodology · Tools support · Web design

27.1 Introduction

Learning is an inherently subjective process; the learner constructs her own knowledge possibly different from representations of the others [7, 8]. Discussion and experience exchange constitute an essential component in learning [13]. Social learning strategies involve mutual reflection, confrontation, and resultant alignment of the individual knowledge constructs with the aim to reinforce the quality of learning.

While the benefits of social learning activities are apparent, it is not so apparent how exactly they should be combined with the learning process and what methodology and supportive tools are needed for their successful implementation. Further questions arise in blended learning contexts, where the students also

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naturally communicate in person, and they may not be motivated to employ specific tools such as online discussions. If the students are not motivated well enough, it may not be efficient to engage them in such activities, when measured by improvements of the learning outcome.

In our teaching practice, we faced similar problems. In the past, we tried to involve students in social learning activities using blog articles on topic of the course combined with peer reviews to ensure efficient delivery of feedback and learning experience exchange. However, the students of applied informatics and computer science are not well motivated when it comes to blogging, and hence, we only achieved partial success [1]. In this paper, we report on our experience with changes introduced in the recent course run: (a) As the students are much more motivated when it comes to programming and development activities, we have applied peer reviews on top of these activities instead of blogging; and (b) to further boost student's motivation and interest in the feedback phase, we allowed the students to improve their course work according to the peer feedback, before it is submitted for instructor assessment.

This modified methodology was met with higher apprehension by the students, who especially liked the opportunity to revise their submissions based on peers' reviews. As we report in details, we have observed improvements in learning outcomes. When we compared the students' reviews with the consecutive instructor's evaluation of the improved version, we have seen that large part of the feedback was used by the students.

27.2 Related Work

Peer review was successfully integrated into education several years ago [12]. A frequent form of reviewing activity is peer assessment of writing (essays, technical writing, blogs, etc.) [5, 14] or oral presentations [6]. Gehringer [3] successfully used peer review also in other educational activities such as creating test questions, collecting sources related to the course topic, making up a problem on some topic, and animation design. Peer review is widely utilized in MOOCs not only as a method of assessment but also as a formative learning activity [2, 9]. Other works concentrate on tool support for peer review, e.g., Popescu and Manafu [10] extend DokuWiki with various peer review and peer assessment features.

A distinctive point in our experience report is the application of peer reviews on the project work in the area of Web design in a blended learning scenario. In addition, we put strong focus on both methodological issues and learning outcomes, and also on the supportive tool (as described in a separate paper [4]).

27.3 Course and Project Assignment

This study focuses on a Web design course that is part of master curriculum in applied informatics. The course is also popular with many bachelor students, who take it voluntarily. In the current year, 37 master and 26 bachelor students were enrolled.

The course focuses on front-end Web design issues (i.e., not the back-end programming) including both desktop and mobile Web sites and concentrates predominantly on Web design methodology (e.g., prototyping, usability testing, and user-centered design) and Web quality standards (accessibility and usability, content quality standards, etc.).

The course activities are split into lectures, practicals, and project work. During the semester, the evaluation consists of written exams (midterm and final), extra points earned for activity during the practicals, and the project.

During the full-semester project assignment, the students independently develop a Web application (personal blog with typical blog features), in both desktop and mobile versions, thus including sufficient amount of meaningful content. This is split into three phases, each of which is evaluated independently:

1. Back-end and desktop layout: The back-end is not evaluated (there are other courses which focus on this). The focus is on the quality of the layout, especially inclusion of all typical blog features in the usual place, clean visual logic and comprehensibility by the user, and robustness.
2. Mobile layout and navigation conventions (both desktop and mobile). The focus is especially on proper development of mobile layout for small screens and touch interfaces, contextual switching between mobile and desktop, and proper implementation of basic navigation conventions on both versions.
3. Content quality. The students have to develop some demo content for this phase, which is evaluated w.r.t. Web publishing standards and quality criteria (e.g., writing style, proper usage of HTML markup, Web content accessibility standards). This is the most difficult phase, as the number of requirements is quite high, and many students tend to trivialize them (as they prefer to focus on programming).

The project offers the space for hands-on practice for most of the knowledge and skills the students are supposed to master during the course, and it also serves as the primary form of assessment for this practical part. Therefore, we put a lot of emphasis on it, and it is our aim to increase the time spent on this assignment as much as possible. In the past runs of the course, the assignment was only evaluated as one final submission. We observed that the students only started to work on the project a few days before the deadline. Several years ago, we split the project into three phases, which resulted in an increase in the time spent working on the assignment, and improved learning outcomes. To further improve this, this year we complemented each of the phases with a peer review round, as we explain in the next section.

27.4 Peer Review Methodology

We chose to use peer reviews, as they were previously shown to increase students' contact time with the course matter, and to foster experience exchange, and thus improving learning outcomes. We added a peer review round after each project phase. Each submission in each phase was randomly assigned three reviewers. The review was blind, but not double-blind (i.e., the reviewer knew the identity of the submission authors, but not vice versa). The reviews were delivered using a structured review form, which was different in each of the three phases. The questions in the form were directed toward the goals of each phase, and they more or less covered the evaluation criteria used by the instructors, but were often differently structured.

We list a sample of questions from the second phase: (Q1) Is there a truly mobile version of the site with seamless automatic switching? (Q2) Does the mobile version properly accommodate small screens? (Q3) Are all functional elements properly supporting touch screen interaction? (Q4) Are main navigation features consistently designed, located where usual, and easy to spot? (Q5) Is most relevant navigation contextually repeated where it is useful? (Q6) Is the user's navigation context aided as much as possible? (Q7) Does each page contain all required information to act as a freestanding entry point to the site?

The reviewer had to answer each question with a rating ranging from 1 (very poor) to 5 (excellent), and in addition to provide a verbal justification for the given rating, of minimum 100 characters. The rationale behind this minimum limit is to encourage students to give more extensive feedback, e.g., also in cases when they had no objections.

Students who missed the submission deadline were not allowed to review in the given phase. The aim of this rule was to avoid the situation in which there were very few submissions but too many reviewers. The reviewing phase took approximately 3–4 days. Afterward, the reviewing was closed, and the students were given additional 3–4 days to process the reviews and incorporate the feedback into their submissions before the submissions were in fact evaluated by the instructor.

All in all, we hypothesized the following expectations of how the reviewing process may contribute to the learning outcomes: (a) Students spend more time working on the assignment, as in fact the number of deadlines is doubled (including the additional deadline for the corrected version). (b) Students gain better understanding of possible problems with their work due to the feedback from their peers. (c) This understanding is further reinforced by active participation in reviews while inspecting the work of the others and comparative reflections to their own solution. (d) We also hoped that students would turn in their submissions in more complete shape due to being pressed by the fact that their own colleagues will be inspecting them.

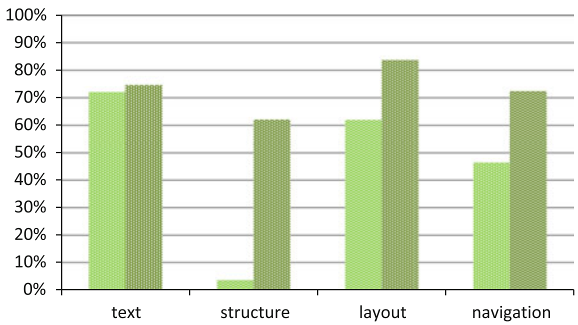
27.5 Results

We first compared the average project results between the years 2013 and 2014. We assumed that as peer reviews were now coupled with the project, this would contribute to better understanding of the subject matter. Together with the newly introduced option to improve the project based on the feedback from the reviews, this could contribute to better outcome from the project. Since the project evaluation methodology was slightly adjusted between the years, we selected four evaluation categories that could be matched: writing style and text formatting (*text*), document structure (*structure*), layout quality (*layout*), and navigation features (*navigation*) for the comparison. All four categories achieved an improvement (Fig. 27.1), which was significant in three of them. The especially high improvement in the structure category (58.4 %) can likely be related to the new detailed question targeting this issue that we added in the review form due to students' bad performance in this category in previous years.

We further wanted to find out whether the possibility to correct the project according to the reviews before the evaluation was helpful to the students, i.e., if the resubmitted projects were really improved. We considered a submission to be improved, if its peers' average rating was poor and the instructor's rating was good. Due to students' tendency to rate their peers higher than the instructor does, that is well known [3], we set both thresholds (for poor reviewer's rating and for good instructor's rating) as 50 %. In total, there were 127 reviews with poor peer rating which corresponded to 84 submissions. Thirty out of all these submissions received good instructor's rating. Almost in all of these cases, students made corrections according to reviewer's comments. Therefore, we think that the students who follow their peers' reviews in order to improve their projects learn more and have a good chance to score higher in the instructor's evaluation.

As a secondary verification, we looked at the Spearman's correlation [11] between the project results and the exam results. The practical assignment should contribute to the learning process; hence, the students who invest a lot of effort in their project (measured by the project evaluation) should learn more and score higher in the exam. Indeed, this value is not directly related to the peer reviews, as it

Fig. 27.1 Average scores for particular project features in 2013 and 2014 (in %)



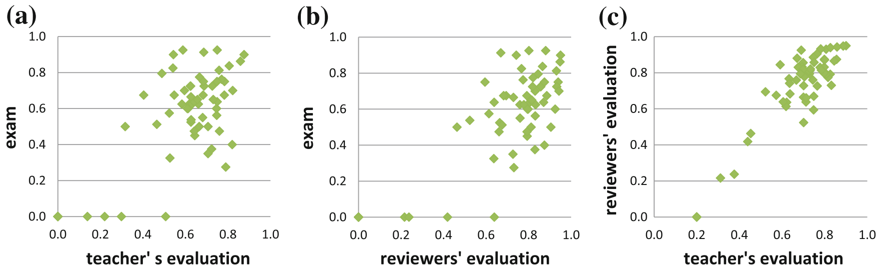


Fig. 27.2 Correlations between **a** exam score and teacher's rating, **b** exam score and students' rating, and **c** teacher's and students' rating

is related to the whole project assignment; however, as we do claim that peer reviews should make the project assignment more effective, we should get a reasonably high correlation. Figure 27.2a depicts the correlated data, and the resulting correlation coefficient is 0.69 (i.e., strong relation).

Afterward, we studied also the correlation between the overall student's rating from the received reviews and the exam score. The data are depicted in Fig. 27.2b, and the resulting correlation coefficient is 0.76 (i.e., strong relation). This latter result suggests that the peers' reviews were relevant (when compared against the instructor's evaluation). To further confirm, this we correlated the instructor's evaluation with the student's reviews Fig. 27.2c. In this case, the correlation coefficient is 0.9 (i.e., very strong relation).

27.6 Discussion

We have seen that in the last year, when we followed the new methodology, the learning outcomes from the project improved in relevant categories. This methodology also permitted the students to improve their submissions based on the received reviews, which proved to be an important point. By detailed inspection of the reviews of selected submissions that showed significant improvement in rating (student's rating from the review compared to the instructor's evaluation after the improvement based on the feedback phase), we found that these students indeed benefited from the received feedback.

We also observed that the correlation between the project evaluation and the exam was strong. This talks only indirectly about the peer reviews; it assures us that in fact engagement in the project assignment as a whole leads to better performance in the exam (i.e., improved learning outcome). Another interesting result is the very strong correlation between the instructor's evaluation of the feedback and the students' numeric rating from the peer reviews. This indicates that the peer reviews are relevant.

Based on an anonymous survey, we learned that the students themselves found the new methodology rather useful, especially the opportunity to use the reviews to improve their projects and consequently to get better grading. Thus, we believe that it also contributed to the students' overall acceptance of this type of assignment. However, it has to be noted that some students tended to abuse this option and submitted very unfinished projects for the peer evaluation, knowing that they can still finish them later on.

Finally, we would like to highlight the importance of tool support for this kind of methodology to be practically implementable. We used our own peer review system that is described in a separate paper [4].

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Chapter 28
ICT Architecture for Supporting Elder Employees to Make Conscious Decisions Under Time Pressure

Ionut Anghel, Tudor Cioara and Ioan Salomie

Abstract This chapter proposes an innovative architecture to provide services for supporting and helping working elders to analyze, visualize, and comprehend the situation they are facing, to take decisions under intense time pressure and to enact the intergenerational knowledge transfer of competencies based on experience to younger employees. Innovative ICT techniques are proposed for developing the functionality of the envisioned services. The social and economic dimension of the proposed solution is assured by reducing early retirement among older decision makers, thus strengthening economic and industrial base.

Keywords Architecture · Conscious decision making · Elder employee

28.1 Introduction

Studies have shown that EU labor force had 62.2 million persons aged over 50 years in 2010 and over 40 % of them are decision makers in their companies [1]. The Europeans are retiring early on average at the age of 61 years. When asked about the causes of their early retirement, most of them have listed among other, working conditions such as intense time pressure and frequent changes in work, difficulty to learn or adapt to new technologies or the fact that their experience is not properly recognized by the younger employees [2]. Studies have shown that

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decision makers do things in different ways when they face the same decision and the older adults have difficulties in selecting appropriate strategies for delaying with new not encountered before situations compared with younger adults [4]. This can be caused by physical, cognitive, and behavioral changes. Also, the proper integration and visualization of information can influence the older employee rational decision-making skill [3].

Contemporary service models [5] for older decision makers aim at providing customized training and specialization courses with the goal of keeping the older employees effective and active at their workplace. Existing training services [7] aim to teach older people to be more flexible and comfortable with new technologies. Also they allow older workers to gain work experience and train in areas of their choice to eliminate the fear of being fired and keep their self-esteem and self-confidence [6]. None of existing service models to our knowledge addresses the difficulties in dealing with decisions taken under intense time pressure as an important component of older employees “deficit model of age.” The contemporary service models do not offer real-time situation comprehension and cognitive support in the working environment for older employees taking fast decisions. They lack of older employee situational awareness and reactive components which is critical in easing their jobs and working conditions. Also they do not offer support for evaluating a decision and for creating, organizing, and disseminating decisions, thus intergenerational knowledge transfer based on experience cannot be achieved.

This chapter addresses these problems by proposing the development of an innovative ICT system-based advanced data analysis and AI decision making to provide services for supporting and helping working elders to take decisions under intense time pressure, to ease new technology learning and to enact the intergenerational knowledge transfer of competencies based on decision experience to younger employees.

28.2 Support System Architecture

Figure 28.1 presents the service-oriented architecture of the system and innovative ICT techniques used for each service development. It is designed based on a self-adaptive control loop and will be capable of environment and situation perception (Data Monitoring Service), situational interpretation (Data Analysis Service), and reactive behavior (Decision-Making Service and Knowledge Transfer Service).

Data Monitoring Service will sense and collect data regarding the older employee which may influence the quality of judgment or decision under intense time pressure, the decision faced and the context in which the decision need to be made. An *Older Employee Virtual Individual Model* will be constructed and used to describe in a holistic personal profile manner all the sensed data related to the older

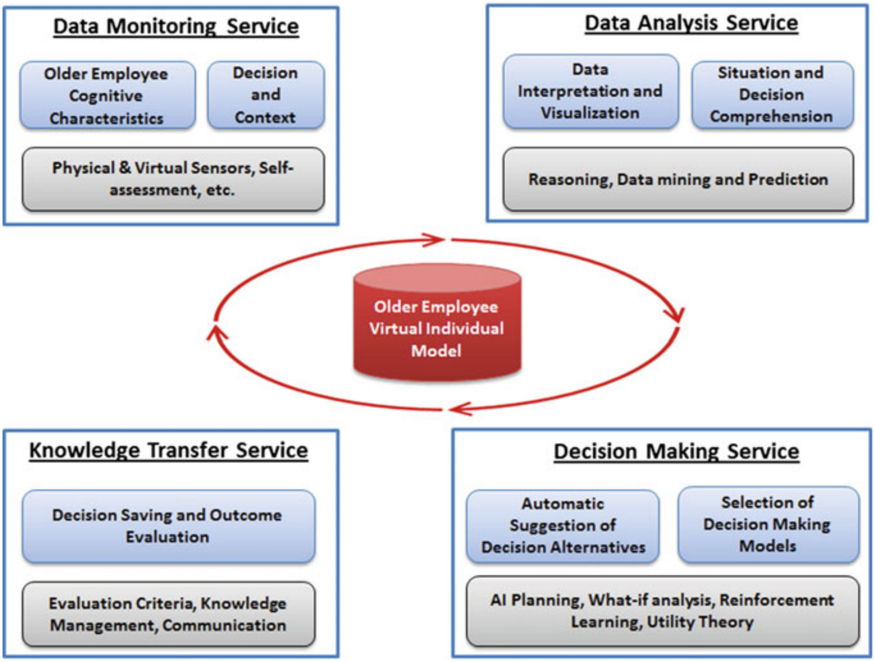

Fig. 28.1 Proposed system conceptual architecture and support services

employee. The model will be implemented as ontology, thus enacting the semantic interoperability between all services and offering a common vocabulary and understating of older employee characteristics, decision faced, work motivation, cognitive processes, etc.

Data Analysis Service will provide data interpretation and visualization features as well as decision comprehension techniques. The data interpretation and visualization techniques will be applied on the sensed data aiming at helping older employee to determine the options available for a decision, to assess the positive and negative consequence of each alternative, and to identify relevant probability and importance of an event. Decision comprehension techniques will assist the elder in understanding and integrating factual information provided by data interpretation/visualization techniques and for evaluating under intense time pressure the decision they are currently facing.

Decision-Making Service will allow for selecting in an automatic manner the decision strategy that fits best with the elder cognitive characteristics and with the specific of the current decision. AI-based cognitive decision-making functions based on decision trees, what-if analysis and reinforcement learning will be used.

Knowledge Transfer Service/Portal will allow the older employee to assess the quality of a certain decision, to save and transfer it to younger employees.

28.3 Usage Scenario

Let us consider a company that has a semi-automatized production line of high-voltage transformers. John is an elder decision maker on production line that need to take fast and good decisions, failures having as consequence loss of money and injuries. The knowledge gained in 20 years working in the company is extremely valuable and the company is interested to keep him active as long as possible. With the passing years, his motivation, attention, and responsiveness are getting weaker and he needs customized assistance to take decisions. The *Data Monitoring Service* will collect data regarding his stress level, emotion, and health from the production line (i.e., oil pressure and temperature in transformer, liquid density and flow, and voltage). To take a quick decision, John demands to visualize data regarding each transformer production and testing process customized to his cognitive abilities (e.g., verbal information-processing rather than numeracy). This helps him better comprehend the situation in which a decision needs to be made (i.e., oil low pressure in transformer, isolation failure, and montage failure). John accesses with his mobile device the *Data Analysis Service* which not only displays data customized to his abilities, but also provides necessary tools to determine the positive and negative consequences of each decision alternatives on the production capabilities or product quality. The analysis of the monitored data will help John in assessing problem cause. For example, a leak in the radiator may cause the oil level to drop below the radiator inlet or in other cases is due to blocked coolers and malfunctioning cooler controls. If John demands support and assistance from the *Decision-Making Service,* the service will select a decision strategy customized to his cognitive abilities and will provide in an automatic and proactive manner a suggestion regarding the current decision. After a decision is taken, the production is continuously monitored and John can use the *Knowledge Transfer Service* to assess the quality of the decision and pass this knowledge to younger employees.

28.4 Conclusions

In this chapter, an ICT system for supporting older employees to cope with decision process under intense time pressure was presented. Due to its ambitious objectives, it will have a significant *social and economic impact* by: (i) reducing the early retirement among older decision makers helping them to stay active longer as their life expectancy will increase, (ii) strengthening the economic and industrial base through intergenerational knowledge/experience transfer to younger employees, and (iii) improving work quality and effectiveness leading to better quality products and services which are associated with direct benefits for the consumers of the products and the society as a whole.

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Chapter 29
Study on Teacher–Student Interaction in Flipped Classroom Based on Video Annotation Learning Platform

Qi Zhang and Fati Wu

Abstract Although "flipped classroom," as a new teaching model, has attracted the attention of many researchers at home and abroad, very few researches have focused on the teacher–student interaction in flipped classroom. To study the teacher–student interaction, we adopted two different teaching models to complete a teaching task in two different classes with the same grade and the same major, respectively. Based on the analysis of the two videos filmed in the two classes, we made comparisons of the teacher–student interaction between two methods with the help of FIAS (Flanders Interaction Analysis System).

Keywords Flipped classroom · Video annotation learning platform · Flanders Interaction Analysis System

29.1 Research Purpose

The purpose of the research is to study and discuss whether flipped classroom model, with the support of video annotation learning platform, can improve teacher–student interaction and whether it can stimulate students' interest and motivation.

29.1.1 Flanders Interaction Analysis System (FIAS)

According to FIAS, classroom teaching activities are mainly organized by the way of verbal behaviors. Also, the classroom interaction between the teachers and students is classified. Analytic data can be obtained by analyzing the matrix, which

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provides important basis for evaluating and improving teachers' teaching quality. FIAS can also be employed to analyze the classroom interaction of information technology application. The analytic process is simple and easy to operate [1].

29.1.2 Video Annotation Technology

More and more researchers describe pedagogic scenarios where the use of a video annotation tool could be of added value to the students' overall learning process due to its great expressiveness. These annotation tools allow learners to add their comments and pop questions in particular time.

29.2 Method

29.2.1 Participants and Design

In the experiment, two different models, namely traditional lecture model and flipped classroom model, were adopted by the same teacher with 12-year teaching experience to instruct the same content (The Humanism Learning Theory). The length of teaching time was one class time, 40 min. In the traditional lecture model, the teacher adopted the Instructional Strategy of Robert Gagné's nine events of instruction. In the flipped classroom model, before class, the teacher uploaded the micro-video to the video annotation learning platform and set embedded exercises. Then, students watched the video lectured and took down the notes. Also, students questioned and sent their messages to the teacher through the platform when coming across any difficult problems. During class, the teacher answered these questions together and provided targeted guidance in the classroom. Besides, the teacher raised the questions to generate the group discussion and communication. The whole process of the two classes was filmed, respectively, for later analysis.

29.2.2 Video Annotation Learning Platform

As shown in Fig. 29.1, the platform employed three kinds of annotation, namely "embedded exercises," "notes," and "questioning."

"**Embedded Exercises**": When the video comes to the marked point, it will pause and some objective questions will pop out for students to answer. The answers are graded according to the degree to which the answers given by students match those pre-uploaded by the teacher.

"**Notes**": When students add notes, the video will pause, leading to the connection of the current video content with the notes. A single video can be noted many times.

Fig. 29.1 The video annotation learning platform (VALP)

"**Questioning**": Students can ask questions by sending messages to the teacher through the platform whenever they need.

29.2.3 Data Analysis

The videos filmed in the classrooms were played with a pause of every 3 s and two researchers got the analysis data of every 3 s. The methods of data collecting and counting could be found in Refs. [2, 3]. Figure 29.2 shows the analysis matrix of

"Flipped classroom model" based on VALP

"Traditional lecture model"

CODE	1	2	3	4	5	6	7	8	9	10	SUM
1	2	0	3	3	1	0	0	0	0	1	10
2	0	2	2	4	0	0	0	0	5	2	15
3	3	0	2	8	4	1	0	5	13	2	38
4	1	1	4	121	13	33	0	19	6	5	203
5	0	0	3	23	116	19	0	2	0	0	163
6	0	1	0	3	19	41	0	11	21	0	96
7	0	0	0	0	0	0	0	0	0	0	0
8	1	2	3	8	4	0	0	78	24	2	122
9	3	7	19	29	5	0	0	4	57	4	128
10	0	2	2	4	1	2	0	3	2	0	16
SUM	10	15	38	203	163	96	0	122	128	16	791

Fig. 29.2 Flanders interaction analysis matrix of flipped classroom

Flanders Interaction of flipped classroom. The number of each cell in the matrix, respectively, represented the frequency of each speech act in a class. The proportion of teacher talk, student talk, invalid language, teacher questioning, and student speaking was calculated.

29.3 Results and Discussion

29.3.1 Proportion of Teacher Talk and Student Talk

The results revealed, in the traditional lecture classroom, teacher talk accounted for 84.3 % while student talk took up 8.1 % and invalid language tool up 7.6 %. In the flipped classroom, the proportion of teacher talk was 66.3 % while student talk accounted for 31.61 % and invalid language accounted for 2 %, showing that students in the flipped classroom were more willing to express their ideas.

29.3.2 The Proportion of Teacher Questioning and Student Speaking

The results revealed that in the flipped classroom, the proportion of teacher questioning was 55.5 % and the proportion of student speaking was 51.2 %. However, in the traditional lecture classroom, the proportion of teacher questioning was 5.8 % and the proportion of student speaking was 3.2 %.

29.3.3 The Function of Teacher Talk

The effects that the teacher exerted on students could be classified into two kinds: direct effects and indirect effects. If the ratio of indirect effects to direct effects is greater than one, it showed that the teacher tended to control students indirectly in the classroom; otherwise, he/she tended to control students directly. The results we got from the experiment showed that in the traditional lecture classroom, the ratio was 13.8 % while the figure in the flipped classroom was 102.7 %.

29.3.4 Teacher–Student Interaction Model

The closed loop structure formed by cell (4-4), (4-8), (8-4), and (8-8) in Fig. 29.2 embodied the "lecture-practice" teaching model. The closed loop formed by cell

(3-3), (3-9), (9-3), and (9-9) embodied the “inquiry-innovation” teaching model. As could be seen from the marker line in Fig. 29.2, lecture classroom was in accordance with the “lecture-practice” teaching model and the flipped classroom was in accordance with the “inquiry-innovation” teaching model.

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Chapter 30
Design and Implementation of Self-regulated Learning Achievement: Attracting Students to Perform More Practice with Educational Mobile Apps

Vahid Bahreman, Maiga Chang, Isa Amistad and Kristin Garn

Abstract This study investigates the design and implementation of the self-regulated learning-based achievements. We aim to incorporate the SRL-based achievements in educational mobile apps to attract students to perform more practice with mobile applications. The review of SRL literature shows several research communities' efforts regarding assessment and improvement of human learning experience in a computer-assisted learning environment. Researchers in educational psychology have developed theories of human cognition. In addition, researchers in computer-based learning environment (CBLE) as well as researchers in machine learning (ML) seek ways to improve human–computer interactions. This research incorporates some of the designed features in a mobile application named Practi. The Practi app is a commercial product and is a mobile software application which allows students to perform math and science practice designed and provided by school teachers. To show that the designed SRL-based achievements are implementable, this research also develops a simulation program.

Keywords Cognition · Metacognition · Motivational constructs · Feedback · Scaffolding · Personalized · Reflection · Active learning

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30.1 Introduction

A shift from classroom-based learning environment to computer-supported learning mechanism requires students to regulate their learning. Self-regulated learners (SRL) take control of their own learning. They set goals and choose strategies to achieve those goals. They may need to modify their strategies when they find the preset goals far from reach. In some cases, they need to abandon their goals and set new sets of goals based on new conditions [1].

In the quest for a more effective education system and in the absence of teachers in computer-based learning environment, computers play a key role known to researchers as MetaTutors. MetaTutors record and trace student progress. The MetaTutor also provides students with timely and explicit feedback [2]. Researchers in educational psychology introduced new forms of feedback known as cognitive feedback that is provided to students during their task engagement in a timely manner as the task unfolds [3].

This research makes similar efforts to develop criteria to create implementable SRL-based achievements. These achievements provide students with required cognitive and metacognitive skills in learning rich-domain concepts. The developed criteria are bound to the indexes available to evaluate a student performance during the student's engagement with a learning task.

Section 30.2 demonstrates the SRL-based achievements this research designed. Section 30.2 also shows and explains the simulation program this research developed for proving that the SRL-based achievements are implementable into the Practi app. At the end, Sect. 30.3 makes a brief summary and discusses possible follow-up research that could be done in the near future.

30.2 Design of SRL-Based Achievements

This research aims to design achievements to encourage students to engage in performing more practice with the educational mobile app Practi. Nine self-regulated learning theory-based achievements are designed as summarized by Table 30.1.

- Self-regulated learning theories find that students become more engaged in a learning task when they see significance of skills they acquire for completing the learning tasks. In other words, students with an understanding of task objectives are more successful in terms of completing the task. This research designs a Task Significance achievement to reward students for paying attention to task objectives and penalizes them by deducting points when they ignore it.
- The theories also emphasize that students make consistent efforts in terms of accomplishing all task objectives. This research designs a Consistency achievement to award points proportionate to students' progress in doing a quiz.

Table 30.1 The SRL-based achievements and the corresponding evaluation criteria

Correspondent SRL theory	Achievement name	Criteria
Motivational constructs	Task significance	Skipped (Y/N)? (2 pts ↓/x pts ↑)
Motivational constructs	Consistency	x pts ↑ for 25 % progress
Metacognition	Interest	x pts ↓ for % Qs skipped
Cognition	Technique	Q(t[ave]) > x(s) ↓ x pts
Feedback	Accessory	x tips seen ↔ x pts ↓
Stress management and volitional strategies	Focus	[Qs(ans)/Qs(all)] ↑ x % ↔ x pts ↑
Set, manage goals, and follow instructions	Compliance	[t(finished) ↔ t(preset)] t(x sec.)↑ ↔ x pts ↓
Metacognition	Knowledge	[Ans(correct)/Ans(total)] 25 % ↑ ↔ x pts ↑
Reinforcement and expectancy value	Effort	[Ans(wrong)/Ans(total)] x % ↑ ↔ x pts ↓

- This research also designs an Accessory achievement that allows students to see tips when they are stuck at a step of completing a task. Students, however, lose their score for seeing tips.
- The degree to which a task grasps a student's attention is relevant to the student's interest in the subject. This research achievement, namely Interest correlates with the number of questions a student skips while taking a quiz.
- The average time students spend on solving each question in a quiz is another measure of students' metacognitive skills. This research designs a Technique achievement to award or penalize students accordingly.
- A Focus achievement is used to measure the degree to which a student manages his or her stress level during a quiz and determines how well the student performs in the quiz.
- The Compliance achievement measures the commitment to the application of self-regulated learning skills, which define students' success in computer-assisted learning.
- A final achievement, namely Knowledge, simply evaluates students' knowledge of a subject based on the ratio of correct answers that students receive in a quiz.
- Reinforcement theory illustrates that a person's behavior is a product of the environment the person grows up in. We design the Effort achievement to measure when a student makes an effort, regardless of the result.

This research aims to design SRL achievements for the educational mobile app—Practi. By integrating SRL-based achievements into Practi, the upgrade makes Practi capable of awarding points to students so they can unlock more features and virtual trophies according to the improvement of their performance. The students can also receive feedback when they are engaged in a task and consult with tips to boost their performance. The number of tips have been checked by students becomes an index

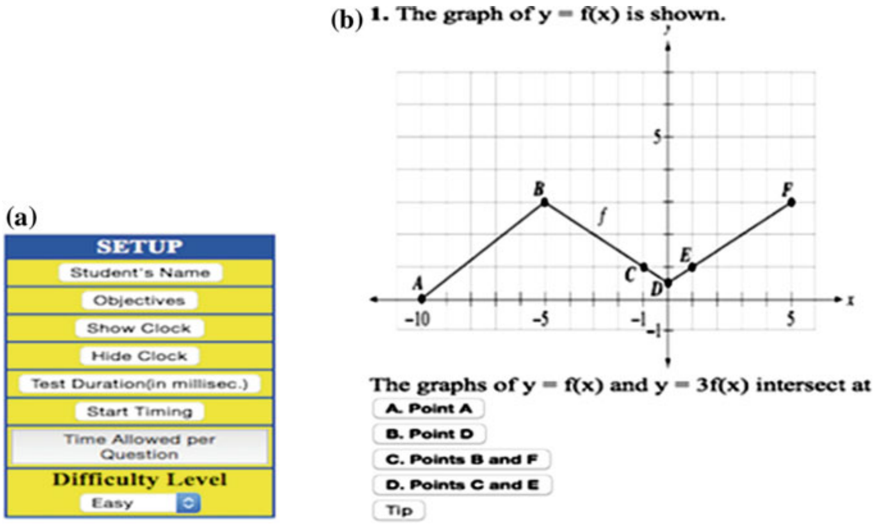

Fig. 30.1 The simulation program

for Practi to compute students' individual and overall scores. Students are also allowed access to more difficult quizzes when needed. As soon as students complete a level with a noticeable performance increase, the upgraded Practi unlocks student access to a more difficult quiz level.

The research team has developed a simulation program to implement the designed SRL-based achievements to prove the possibility of implementing the proposed design. We use questions from Alberta's high school Math diploma examination bank to create the quizzes for the simulation. Figure 30.1a shows the simulation program that allows researchers to simulate a student setting-up objectives, choosing quiz difficulties, and answering questions in a quiz. When students are answering a question, they can view a tip if they want as Fig. 30.1b shows. Once the students complete a quiz, they can check their overall and individual achievement scores as Fig. 30.2 shows. John lowers his score by seven points for spending too much time on task objectives. The achievement criteria deduct 1 point for each additional 5 s increment beyond the maximum allowed time that John spends on the task objectives. John is also awarded 6 points each time he progresses 25 % in doing the quiz. He also receives 18 points for his achievement consistency. Each time John skips 5 % of the questions in this quiz, his Interest achievement receives a − 2 point deduction. Likewise, other achievements are calculated for John by the program based on the criteria shown in Table 30.1.

	Task Sig.	Consistency	Interest	Technique	Focus	Compliance	Knowledge	Accessory	Effort	Total Score
John	-7	18	-2	-5.22	3	-2	12	-0.8	-0.4	15.58

Fig. 30.2 Student achievement score per SRL category

30.3 Conclusion

This research designs SRL-based achievements based on the result of reviewing SRL literature. In order to demonstrate the possibility of implementing the proposed design in the existing educational mobile app, Practi, a simulation program is implemented. We recognize the importance of equipping students with SRL skills in the transition from classroom learning to computer-supported learning environments. Ultimately, we see the possibility of implementing this set of tools and skills to help put students on a road to success utilizing mobile technologies.

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Chapter 31
MUSIX: Learning Analytics in Music Teaching

Claudia Guillot, Rébecca Guillot, Vive Kumar and Kinshuk

Abstract This chapter exposes MUSIX, an analytics tool about to be developed, that will enrich music learning and enhance the music teaching approach. MUSIX will collect data from music theory lessons, the playing of instrumental pieces, sight-singing, and vocal training, and subsequently teach and help each student through computerized analysis to better themselves. This software will offer precise instructions, exercises, games, and quizzes to fill in gaps and build a strong understanding using self-regulation and co-regulation techniques. Computer software, audio recording, and MIDI connection between the instrument and the computer are different means that will be used to track the results that will be analyzed and then displayed in a compelling dashboard.

Keywords Music analytics · Teaching approach · E-learning · E-teaching · Audio software · Human–computer interaction

31.1 Introduction

This chapter aims to propose an alternative to learning music successfully through the development of a music analytics software that will provide a clear understanding of the progress or gaps in a student's learning while offering solutions to fill in those gaps. Research on music has proved "the potential impact of music edu-

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cation on enhancing learning skills and scholastic achievement (Hallam 2010; Portowitz et al. 2009)." [1]. Still, to be impactful, this learning area has to be well monitored since "monitoring student growth and providing scaffolds that shed light on the next step in the learning process are hypothesized to be essential elements of Assessment for Learning that enhance cognitive and metacognitive strategies" [2]. Many techniques have already been used in music teaching, such as "the In Harmony program" that "proposed a multi-layered model for children to study music using computer technology," [1] but how could we go a step further by constantly accompanying students along their music learning process and help them perform at their utmost level using technical and computerized analysis? MUSIX will work toward this learning analytics approach offering constant monitoring solutions, rewarding students' efforts, and guiding them through specific exercises according to their explicit needs, thus building strong future musicians. MUSIX is an online application that will engage students through highly animated and interactive lessons, offering them guidance through multiple paths of learning thanks to its individualistic approach, allowing them to assess their progress through a deep and continuous analysis when playing their instrument or doing other music activities.

This chapter will expose the potential power of a music analytics tool through the aspects of music theory, vocal training, instruments playing, and practice time.

31.2 MUSIX in Music Theory

The goal of MUSIX is to capture and analyze the answers to exercises, quizzes, and tests before displaying the results of these analysis in a dashboard, thus allowing to evaluate each step in the music theory learning process such as the notions of notes, figures, rhythms, symbols, terms, compositors, and more. Additionally, time-stamped data will allow to detect time gaps during a student music theory exercise and will help to pinpoint trends of either lack of understanding or frequent distractions. Whenever a student faces learning difficulties, MUSIX will recognize the exact aspect that needs to be reinforced and will select and propose additional activities or exercises that will strengthen the pinpointed concept thus providing motivation to the student as he/she overcomes each difficulty one at a time. Furthermore, understanding that "teacher feedback provides students an understanding of the gap between their current performance and the learning goals they are aiming for," [2] MUSIX will provide constant feedback during music activities done by the student.

31.3 MUSIX in Singing—Vocal Training

With MUSIX, the sight-singing and vocal training analyses will be performed using computerized audio technologies. In these areas, students will see on their computer's screen a given melody and with an audio software they will sing it while recording themselves. The audio recording will then be compared against the original melody showing the notes that have to be adjusted in the student's singing. This process will help students to improve their accuracy of notes, pitches, and rhythms. MUSIX will always customize the learning process. For example, if the analysis shows that a student struggles regularly to sing a third accurately, MUSIX will provide additional step-by-step exercises to help the student improve this particular aspect before letting him/her continue to the next level of exercises.

31.4 MUSIX with Instruments

Students who are playing an instrument could establish a MIDI connection between the instrument and the computer in order to transfer converted data. While playing on a digital piano or a silent violin, the software will capture numerous data such as the pitch, vibration, duration, and accuracy of the notes, and much more. To help students improve their playing, the software will encourage students to practice a particular note until they reach the correct pitch or the correct interpretation. Moreover, piano keys could have sensors that would capture the softness or toughness of a pianist's playing as proven to be an essential part of the professional playing of a pianist. Goebl's study confirms that "the difference between two equally loud piano tones due to type of touch lies in the different noise components involved in the keystroke. These noise components (i.e., finger–key noise) are audible when the key is struck, and absent when it is pressed down." [3].

31.5 MUSIX During Practice Time

To become an accomplished musician, part of the solution is for a student to practice several hours. As reported by Hambrick's conclusion in his study *Deliberate practice: Is that all it takes to become an expert?*, "the bottom line is that deliberate practice is necessary to account for why some people become experts in these domains and others fail to do so." [4]. However, the best organization of practicing time may vary from person to person. MUSIX software will have the potential to sense the time frame during which a student practices, the duration set aside for it, and the results of his/her performance. These data will give input for music students to help them schedule their period of practice for better time–quality ratio. In addition, MUSIX will help to diagnose if a student is confused about what to practice on his/her instrument or if he/she is easily distracted and not using his/her time efficiently. When playing an instrument, the brain has to be fully active on music, as any other thoughts will trigger mistakes. Indeed, Maidhof's results show that "brain potentials elicited by correct and incorrect keypresses of expert pianists differed already 100 ms before keypresses were fully executed, and thus prior to the onsets of erroneous tones (pre-error negativity)." [5]. It is with this perspective that MUSIX will highly value the attention-span and concentration skills in its analysis.

31.6 Music Analytics

There are already hundreds of music apps over the Internet that may be useful to learn music, but MUSIX will bring training to a different level by tracking everything possible during the process through which students are learning music. Everything they do, read, click, write, sing, play, practice, how they do it, when they do it, and why they do it are all data that MUSIX will sense. These large datasets are extremely valuable for an in-depth analysis of the student as a whole. MUSIX will create the profile of each music student by capturing multiple data about their music activity such as the time span they allocate to it every day, the difficulties they encounter, the time they need to complete an exercise, the duration of their practice (instrument or vocal training), the flow of MIDI captured data, the accuracy level when they play or sing, the way they react when doing errors (stop or continue to play), the process they use to fix errors during their practice, the progress curve of a particular piece from day to day, and their ability to concentrate.

31.7 Conclusion

By continually tracking the music activities of a student, teachers are much better equipped to understand a student's overall behavior. It is because of its analytics power (the analysis done with the data captured) that MUSIX will be able to take into account the individual learning curve of every student, constantly customizing it in order to help them improve their musical education efficiently and guide each one of them through the best path for music success. It is expected that MUSIX will create better musicians, enjoying their training process as much as the results. While taking advantage of the precious involvement of a teacher, MUSIX will complement it by accomplishing the impossible human task of monitoring and analyzing simultaneously a significant number of data from the students.

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Chapter 32
Metric-Based Approach for Selecting the Game Genre to Model Personality

Ahmed Tlili, Fathi Essalmi and Mohamed Jemni

Abstract Recently, games are used as a tool for modeling learners. The learner model can be used to deliver a personalized learning experience. Compared to other modeling methods, games are fun and motivating. However, many genres of games exist in the literature. This makes users confused about the suitable genre to use for the modeling process. This paper presents a new metric-based approach to select the suitable genre for modeling the learners' personality. This approach contains 4 steps which are as follows: Identification of game elements, Selection of game elements, Analyze of game genres, and metric for genre selection.

Keywords Personality · Metric · Learner model · Game genres

32.1 Introduction

To increase the learning effectiveness, personalizing a given learning content based on the learners' profile is needed. According to [1], the personalization process requires 3 models which are as follows: (a) Content model contains the structure of the used learning content, (b) Instructional model contains the method used to present the personalized learning content, and (c) Learner model contains information and abilities of learners. This paper focuses only on the last model.

Various personalization parameters, reported in the literature [2, 3], are collected to create the learner model. Among these parameters, we can mention the learners'

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personality. In fact, many researchers highlighted the importance of this parameter in learning. Arockiam and Charles [4] presented the importance of designing e-learning interfaces based on the learners' personality. El Bachari et al. [5] recommended taking into consideration the learner's personality while assigning to him/her the learning approach. This increases his/her learning performance.

On the other hand, to model learners, different methods are used. In particular, researchers used the learners' traces obtained from interacting with the learning environment [6]. In this context, Pablo et al. [7] recommended using games over e-learning systems as a learning environment. This is because they are interactive and motivating. While e-learning systems are not too interactive (only few clicks), this can generate inaccurate traces. However, many genres exist in the literatures such as the ones mentioned in the taxonomies of Wolf [8] and Bates [9]. This can make the modeling process confusing since there are no guidelines about the genre to use. This paper focuses on the learner's personality as a personalization parameter. Also, it aims to answer the following research question: *What is the most suitable genre for modeling the learners' personality*? To answer this question, the paper presents a metric-based approach. This approach applies 4 steps (Identification of game elements, Selection of game elements, Analyze of game genres, and metric for genre selection) to create a metric which will be used to select the suitable game genre.

This paper is structured as follows: Sect. 32.2 presents the proposed approach to select the suitable genre used for modeling the learners' personality. Section 32.3 discusses the approach, concludes the paper, and gives overview about future works.

32.2 Proposed Approach

In the literature, none of the approach helps to identify the suitable genre for modeling the learners' personality. Therefore, this paper presents a metric-based approach to solve this problem. This approach is called *ISAM*. It contains four steps described as follows:

1. *Identification of game elements*: In the literature, there is no upon agreed definition for the term games. Therefore, each researcher presented different game elements. The main purpose of this step is to identify the various game elements presented by researchers.
2. *Selection of game elements*: As the case of the term games, many definitions were given regarding the term personality like in [10, 11]. This step aims to filter and select the needed game elements (from the ones identified in step 1) based on the definitions and features of personality.
3. *Analyze of game genres*: This step aims to analyze and study the different game genres that will be used to model the learners' personality. This allows identifying the different features and characteristics of these genres.

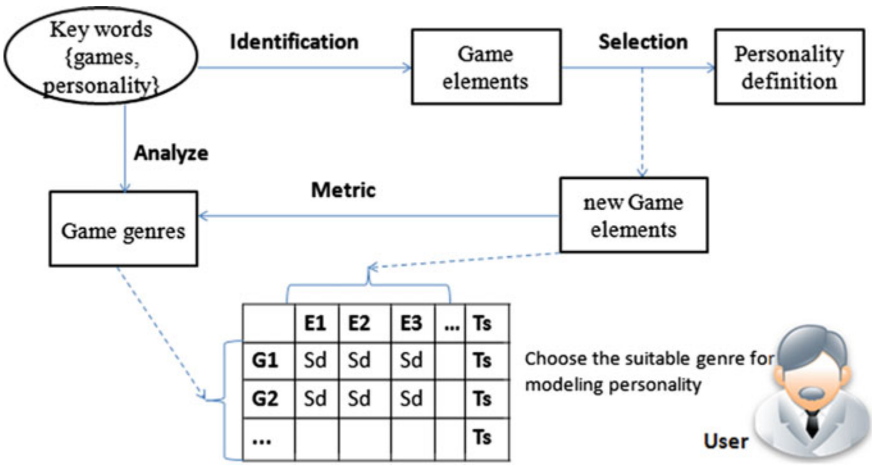

Fig. 32.1 Metric-based approach for identifying the suitable genre for modeling personality

4. *Metric for genre selection*: This step aims to investigate the Satisfaction degree (Sd) of the new set of game elements (selected in step 2) within the game genres (analyzed in step 3). The value of Sd can be given as follows: 0 means no satisfaction, 1 means low satisfaction, and 2 high satisfaction. Then, based on the obtained Sd of each game element in each genre, the Total satisfaction (Ts) of each genre is calculated (Total sum of Sd/total number of game elements). This allows creating a metric which will be used to identify the suitable genre for modeling the learners' personality (the one having the highest Ts).

Figure 32.1 presents the four steps followed in *ISAM*. They are represented with arrows. The element in the circle represents the starting point of our approach. The elements in squares are the terms used during the process. The dot arrow represents the result obtained after a particular step within the process (e.g., the selection of the game elements based on the various definitions of personality gives a new set of game elements that will be used in step 4).

32.3 Discussion, Conclusion, and Future Works

This paper presented a new metric-based approach called *ISAM* to select the most suitable genre to be used for modeling the learners' personality. It consists of 4 steps which are as follows: Identification of game elements, Selection of game elements, Analyze of game genres, and metric for genre selection. The advantages of *ISAM* are as follows:

- It makes the learners' personality modeling clearer using games. This is seen when the user uses the created metric (see Fig. 32.1) to refer to the most suitable game genre for this purpose without going through all the available genres.
- Provides metric for comparing game genres and their elements (see Fig. 32.1). This could be used as a support for the selection of a particular genre based on a specific need.
- Provides metric for comparing the Satisfaction degree of each game element within various game genres (see Fig. 32.1). This can give previous information about the game elements to use while designing a particular game genre.

Future works focus on:

- Defining a generalized metric based on metadata and ontology approach [12]. This metric investigates the Satisfaction degree of all game elements with all game genres.
- Designing a system based on this approach which contains the characteristics and elements of all game genres. Then, based on the given personalization parameter (personality, learning style…), the system chooses automatically the most suitable game genre for modeling that parameter. This will make modeling using games less confusing and more accurate.

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Chapter 33
Toward a Generic e-Assessment Process: Using Cloud Computing

Fahima Hajjej, Yousra Bendaly Hlaoui and Leila Jemni Ben Ayed

Abstract In recent years, e-assessment started to attract a lot of attention from researchers as well as practitioners. There are many problems for the application development of e-assessment such as the difficulty to use the assessment object from a platform to another one. In addition, the domain model reuse rate is hardness to guarantee the consistency between designs and codes. Therefore, to resolve these problems, we need an approach aiming to automate the modeling and coding processes in e-assessment system. The present study describes an approach, based on service cloud computing, for integrating assessment functionalities of different LMSs into a generalized e-assessment process.

Keywords e-assessment · Cloud computing · LMSs · Integration

33.1 Introduction

The e-assessment approach could not be suitable for all types of learners as they present different knowledge profiles and learning behaviors. Some of them need to be assessed on the complete learning materials to evaluate their overall knowledge. Others may only need to estimate their knowledge at a particular stage of the learning process in order to access to the suitable learning material. That is why, we are brought about adapting the generic e-assessment process to the learner behavior.

In fact, to ensure this adaptation, we present a set of mapping rules defined as a composite cloud service. The use of cloud technology in our e-assessment approach

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offers for us many benefits such as interoperability, scalability, and flexibility. In this paper, we propose a generic specification and design approach for e-assessment processes based on cloud computing and learner profile adaptability. This new approach has resulted in a three-step method present in Sect. 33.1.

33.2 Generic and Adapted e-Assessment Process

In [3], we have present the development of a generic e-assessment process using the LMSs [1, 2] and based on the LTSA which we extend by some features required to such development. The generated e-assessment model is specified by UML activity diagram language. The advantages of using standards in learning design have already been pointed out as standards are generally developed for use in systems' design and implementation for the purposes of ensuring interoperability, portability, and reusability. To build this generic e-assessment process, we are brought about following the next steps, as presented in Fig. 33.1:

- ***Step1***: We have studied and analyzed a set of existing LMSs such as Moodle [5], OLAT [4], and LAMS [6]… These LMSs provide several e-assessment tools and not a global e-assessment process. In fact, we have explored the functionalities that they offer to realize the e-assessment.
- ***Step2***: Using the reverse engineering, we define a set of transformation rules from the LMS-specific e-assessment tasks to our generic e-assessment process activities. Then, we use a workflow technology for coordinate these activities.
- ***Step3***: Once the generic e-assessment process is built, it will be personalized according to a learner profile defining her/his level of knowledge. In fact, to specify an adaptive and flexible e-assessment workflow, we propose to refine the generic e-assessment workflow by adding (***AddAC***), deleting (***DelAC***), or editing (***EditAC***) specific e-assessment activities according to each learner profile.

33.3 Generic Process as Cloud Service

In our approach, we specify the adaptation process and the e-assessment process as cloud services. Therefore, we are brought to identify the interfaces, the messages, and the operations of each built cloud service. A cloud service can be specified and invoked through as any Web-based application or service offered via cloud computing. Cloud services can include anything from spreadsheets to calendars and appointment book. Cloud services can be flexibly provisioned and released, automatically, to scale and adjust to the levels of demand. For the customer, the services available usually appear to be unlimited and can be accessed in any quantity at any time. The innovation that this cloud e-assessment system defines the resulting generic and adapted e-assessment process as a composite cloud service allowing

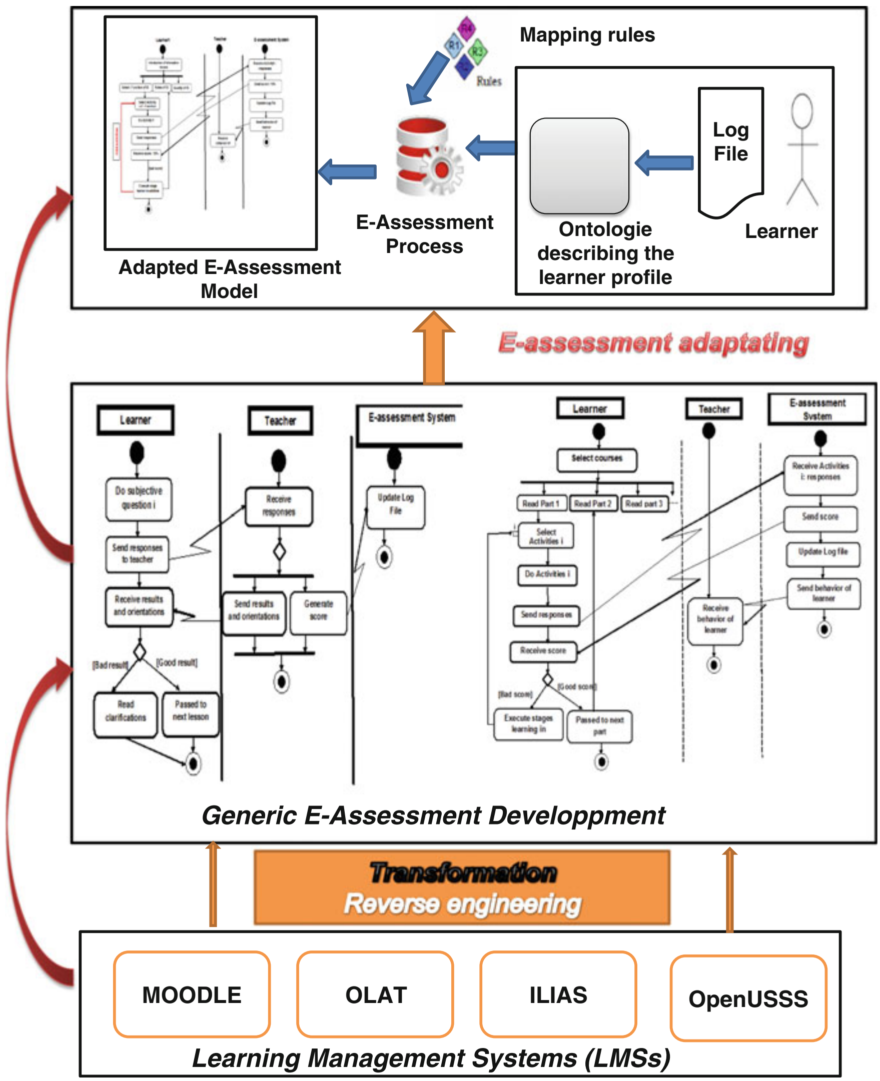

Fig. 33.1 Generic e-assessment process development

flexibility and interoperability between any LMS e-assessment. Our e-assessment cloud is composed of two main composite services. The first composite cloud service, presented in Fig. 33.2, is called *e-assessment generic model*. This service is composed of a set of simple cloud services. Each simple service invokes a generic e-assessment activity.

The second composite cloud service, presented in Fig. 33.2, is called *adaptation process*. This service is composed of a set of simple cloud services. Each simple service invokes an adaptation function presented in the previous section.

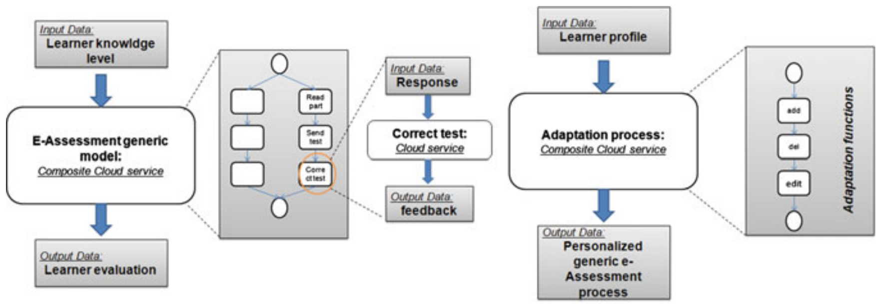

Fig. 33.2 E-assessment generic model: composite service cloud process

33.4 Illustration

In the following, we illustrate our approach with an e-learning and e-assessment scenario applied for the course "*information System.*" The teacher and the learner use Moodle open source. From Moodle, teachers and users can use our platform directly or invoke the cloud services, as shown in Fig. 33.3.

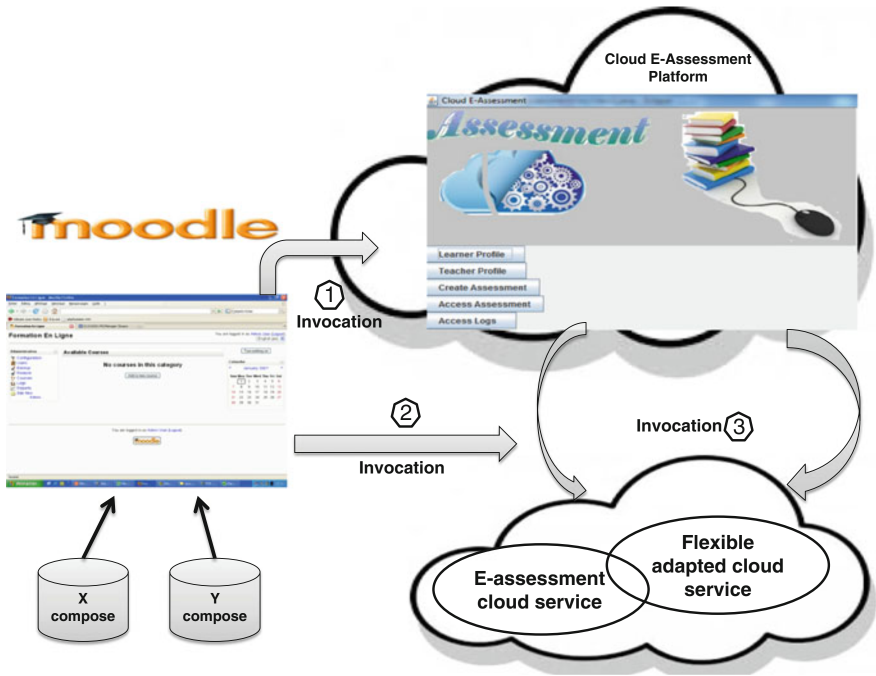

Fig. 33.3 Adaptation process: composite service cloud

33.5 Conclusion

In this paper, we have presented a novel approach for developing generic and personalized e-assessment process for different existing LMSs. This approach is based on the reverse engineering to develop this generic e-assessment process using existing LMS's e-assessment functionality and the LTSA architecture. In addition, this approach uses service cloud computing to improve the interoperability of the use of the adaptation process and the personalized generic e-assessment process.

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Chapter 34
Public Key Infrastructure for e-Assessment

Elisabeth Katzlinger and Johann Höller

Abstract The development and diffusion process of learning management systems have caused sustainable organizational changes concerning teaching and examination proceedings in higher education. This paper deals with the development of organizational and technical facilities for e-assessment at an Austrian University that meets all pedagogical, legal, and (safety) technological requirements. In order to realize these safety-related and legal requirements, a public key infrastructure was installed in a PC laboratory only used for examinations. The technical and organizational solutions support teachers, students, and examination administration equally.

Keywords Public key infrastructure · e-assessment · Examination laboratory · e-learning · Higher education

34.1 Introduction

Due to the implementation of the Bologna Process, many Austrian curricula were converted into the consecutive three-tier Bachelor–Master–Doctorate System. In the course of this process, the curricula underwent substantial change with many courses and corresponding examinations [7]. The assessment of competencies by means of examinations is a necessary precondition for the comparability of qualifications and thus also for facilitating exchange within the educational system [8]. In dealing with e-assessment systems, various dimensions have to be considered in order to guarantee an adequate application of high quality. Thereby, the technical

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solution represents the infrastructure as the basis to develop pedagogical, methodical, and organizational solutions [5]. The article at hand focuses only on the technical, organizational, and legal solutions. Nevertheless, pedagogical and methodical considerations also were considered in the development of the concept. However, they are not the primary focus of the article at hand.

E-assessment means learning progress control using digital media for its preparation, application, and follow-up. Thereby, the (partly) automated correction of examination papers plays a central role [4]. Together with the development of e-learning scenarios, models for e-assessment are developed that are specifically tailored to these developments, such as the integrated model for e-assessment by Wesiak et al. [9]. Also, the level of complexity can vary according to educational objectives as represented in Bloom's Taxonomy [6]. Questions may demand just remembering or request analyzing, evaluating or creating solutions. Teachers and examination administrators benefit from supporting organizational processes around (a large number of) examinations and automatic examination correction. E-assessment systems offer many advantages to students as well, such as quick examination results, fairness, objective grading, feedback, and the possibility of examination review immediately after the examination or pools of questions for mock examinations. Frequently, voiced reservations against electronic examinations are related to pedagogical–methodical aspects (asking for mainly declarative knowledge) [2] on the one hand, as well as organizational–legal aspects, such as the effort of task construction, system reliability, or questions of fairness with respect to students lacking media competence, on the other hand.

34.2 Technical Implementation

A PC laboratory with 62 workplaces and one facilitator's workplace was established, which is exclusively used for electronic examinations. The screens are recessed into the tables (introduced by the University Duisburg-Essen [3]); the 20-cm-high partition walls shall prevent students from putting unauthorized aids onto the desks or peeking to the workplace on their right. In order to prevent students from cheating, additional polarizing filters were applied. The PCs are stored in locked cases to prevent students from shutting down their computers or use personal devices, such as USB flash drives. The examinees' workplaces are equipped with smartcard keyboards. All students of the university are in possession of a suitably coded smartcard (KeplerCard), which actually is their student card and necessary to log in into the individual workplaces. A successful login is registered at the facilitator's workplace and displayed through student number and the photograph of the student card. Furthermore, the screen content of the examinee's workplaces can be monitored at the facilitator's workplace if desired.

The PCs run under the operating system LINUX with a pared-down kernel and a browser. As an application system, a special Moodle instance (Moodle 2.5) runs on the server, which was extended by a specially created module for the integration of the citizen card software (citizen card environment, CEE). This module creates access to the signature generation service of the citizen card environment according to the Austrian e-government standard [1]. The whole examination room is designed for a high level of autarky; thus, all necessary components are in close proximity and secured against failure. For standard examinations, the Internet remains inaccessible. Administrative staff act as proctors, i.e., for potential IT-related questions, a technician is present or can be contacted during every examination.

34.3 Organizational, Legal, and Security Considerations

A successful registration in the Moodle examination course and a valid storage of registration data are necessary prerequisites for taking the examination. This requires an active admission to study on the one hand and—in some courses—the fulfillment of certain requirements. Both prerequisites are electronically checked.

Before the examination starts, a further document is generated that has to be digitally signed by all examinees, which includes the following information:

- A photograph taken by the Webcam of the workplace, which shows the person that actually sits in front of the computer.
- All of the student's master data, including the photograph on the student card and the matriculation number from the smartcard.
- Special examination conditions, such as authorized aids.

This document is digitally signed, which requires the citizen card certificate to be installed on the KeplerCard, and the student has to enter the PIN. Signing this document would not be necessary legally. This step only serves the purpose to ensure that the students fulfill above-mentioned necessary requirements before the examination starts. After a student has successfully signed the document, the actual examination starts. The examination ends because either the examinee decides to submit the examination or the examination time has expired. In both cases, not the standard Moodle function is used, but a specially programmed intermediate step is interposed: The questions asked as well as the answers chosen by the student are shown in a secure viewer mode. The student checks the document and approves by digital signature that the answers chosen are his or hers. At this stage, no changes can be made any longer.

The results are electronically transmitted to the examiner. In case of multiple-choice tests, a list can be generated which can be directly imported into the university's grading management system. All documents created during the examination are available to the examiner during the objection period, for the investigation of either random samples or of suspect cases.

Besides the features of infrastructure mentioned above, which were also decided on from the perspective of establishing a secure examination environment, the following measures are adopted:

- Every 5 s the system makes screenshots, which are saved, in order to be able to reconstruct the different work stages or chosen answer elements, respectively. In case of an error during the final submission, the system alternatively attaches a collection of screenshots from the unsigned document and thus signals that this examination paper needs manual grading.
- When students log into the PC, a photograph is taken by the Webcam, which mainly serves the purpose of documenting changes of the workplace. In order to be able to track their identity on two different workplaces, the pictures taken by the Webcam are necessary.

34.4 Conclusion

The PC laboratory for examinations was established in 2013 and has been available with all the functions and facilities mentioned above. However, already before that a large number of exams of several courses with lower security demands and higher personnel placement were prototypically held in this laboratory. The currently imposed security functions are the result of such experiences. If some of the measures seem slightly exaggerated, it has to be mentioned that they are all based on a corresponding negative experience.

Students especially appreciate that information on their grading is provided much more quickly and that they can immediately run through their results and check, which of their answers were correct and which were not.

Both in the middle and at the end of each term, the examination room nearly reaches the limits of its capacity, without ever having been officially recommended or advertised. Throughout the past two terms, 2120 examinations were taken there at 70 different rounds of examination, which means an average of 30 students per round, whereby on average 26 % more students had previously registered for the examinations. The positive recommendation given by colleagues has once again proved to be an efficient means of promotion.

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Chapter 35
Reflection on Design-Based Research: Challenges and Future Direction

Lanqin Zheng

Abstract Recently, design-based research method has gained more and more attention in the field of education. Although design-based research can bridge theoretical research and educational practice, many problems exist and need to be refined. In this chapter, the problems and the status of design-based research were analyzed deeply. The trends and the future direction of design-based research were discussed in detail.

Keywords Design-based research · Intervention · Design-centered research

35.1 Introduction

Design-based research has emerged as a new research methodology in the field of education in recent years. Situated in an authentic context, design-based research focuses on developing and refining theories of learning and teaching by designing and testing the particular interventions [1]. Grounded in theory and research, design-based research involves flexible design revision and interactions between researchers and practitioners [2]. Design-based research has been applied in many domains, including mathematics and science education, educational technology, and curriculum development [3]. However, many issues and challenges have emerged in design-based research in recent years. The main challenges are addressed as follows:

First, the reliability of design-based research is unclear. The main reason is that design-based research cannot make trustworthy and credible assertions due to the involvement of researchers themselves in design, development, and

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implementation [2]. In addition, the causality is very difficult to be established because so many possible factors are related to research outcomes [4].

Second, due to the contextualized nature of design-based research, only contextual knowledge can be generated and deployed in similar design contexts [2, 5]. In fact, educational research has been criticized for not creating “usable knowledge” [6]. Furthermore, educational researchers have been required to provide scientific and evidence-based claims [7]. Thus, a tension between the request for locally usable knowledge and generalizable knowledge exists in design-based research.

Finally, the findings of design-based research cannot be generalized in other settings. Collins et al. [8] believed that because of the nature of design-based research, the effectiveness of a design in one setting cannot guarantee its effectiveness in another setting. Brown [9] also proposed that design-based research put more emphasis on examining the effectiveness of intervention. Effectiveness measures to what extent intervention resulted in desired outcomes. Therefore, the desired outcomes, however, vary for different researchers and practitioners. Thus, it is very difficult to generalize the findings of design-based research.

35.2 Research Trend of Design-Based Research

In this study, the variation of the research trend from 2004 to 2013 was examined by analysis of 162 studies which adopted design-based research method. These 162 studies were selected from social sciences citation index (SSCI) educational journals from 2004 to 2013. Previous studies have indicated that the analysis of keywords between the two periods can predict the research trends [10]. Therefore, freely available Wordle program (http://www.wordle.net) was used to analyze the frequently appearing keywords so as to shed light on the research trends. Furthermore, the word frequencies evolution based on the full text corpus were automatically analyzed with the aid of WordStat software in order to examine the variation of two different periods.

All of the keywords of 162 papers in different time periods were typed in the Wordle program in order to analyze the research trends. The results indicated that “learning” and “design-based research” were the top keywords that appeared during the different periods. During 2004–2008, the frequently used keywords were design-based research, development research, problem-based learning, collaborative learning, science education, and teacher education. During 2009–2013, the frequently appeared keywords were design-based research, educational technology, development research, instructional design, collaborative learning, and evaluation.

Furthermore, in order to examine the evolution of research trends in the field of design-based research, deviations and significance of word frequencies based on full text corpus were analyzed in the two time periods, as shown in Table 35.1. $Freq_2$, $Freq_1$, and Dev. indicated the frequency of 2009–2013, the frequency of 2004–2018, and the deviations between these two periods. Results revealed that there were significant increases in the following research topics:

Table 35.1 Research trend evolutions based on word frequencies analysis

Words	$Freq_2$.	$Freq_1$.	Dev. (%)	Words	$Freq_2$.	$Freq_1$.	Dev. (%)	*p* (2-tails)
PBL	205	31.6	548.7	Tutor	238	489.8	−51.4	0.000
Mobile	236	57.9	307.4	Web	516	1101.2	−49	0.000
Scaffold	491	147.5	233	Computer	1006	1709	−41.1	0.000
Language	938	447.4	109.5	Software	367	603	−39.1	0.000
CSCL	150	73.7	103.4	Instructor	492	768.9	−36	0.000
Science	2929	1740.6	68.3	Technology	1751	2707.1	−35.3	0.000
Implementation	830	558.3	48.7	ICT	240	175.9	−28.8	0.000
Redesign	227	152.7	48.6	Research	5474	7547.1	−27.5	0.000
Practice	2545	1761.7	44.5	Design	8357	11,578	−26.3	0.000
Collaborative	958	663.6	44.4	Theory	1566	2122.5	−26.2	0.000
Evidence	810	560.9	44.4	Refinement	205	273.9	−25.1	0.000
Intervene	48	34.2	40.2	Theoretical	547	716.3	−23.6	0.000
Learn	8734	6462	35.2	System	1418	1848.6	−23.3	0.000
DBR	364	266.8	31.6	Revision	224	284.4	−21.2	0.000
Development	2132	1672.2	27.5	Curriculum	1123	1406.2	−20.1	0.000
Iteration	304	242.3	25.5	Education	2889	3507.6	−17.6	0.000
Evaluation	978	824.2	18.7	Instructional	1147	1343	−14.6	0.000

- Learning, with the emerged words “learn,” “PBL,” “mobile,” “collaborative,” and “CSCL.”
- Design-based research itself, with the emerged words “DBR,” “implementation,” “redesign,” “intervene,” “development,” “iteration,” “evidence,” and “evaluation.”
- Application of design-based research, with the terms “science,” “language,” “scaffold,” and “practice.”

At the same time, significant decreases were found in the following research topics:

- Technology, with the emerged words “Web,” “software,” “ICT,” “technology,” “system,” and “computer.”
- Education, with the terms “instructor,” “education,” “instructional,” “curriculum,” and “tutor.”
- Revision of design, with the words “design,” “refinement,” “revision,” “theory,” and “research.”

35.3 The Future of Design-Based Research

Based on the aforementioned issues and the status of design-based research, much more effort is required so as to claim success for design-based research. The most important is that the effectiveness of intervention cannot be validated because of the unrepeatable learning activities. It is difficult to recreate the exact learning activities and conditions that other researchers encountered in their own educational research [11]. Thus, the findings of design-based research cannot be replicable in other settings. However, replicability is the fundamental and central idea for scientific paradigm [10]. Therefore, new approaches that can create replicable, scientific, and generalizable knowledge are called for in educational research. Barab and Squire [2] reported that design-based research does not reveal and highlight the crucial value of the design in a particular context. The design activities that can yield very interesting outcomes have been paid less attention in design-based research [12]. Therefore, new approaches should put emphasis on the design itself and how the design functions.

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Chapter 36
Optimal Composition of e-Learning Personalization Resources

Sameh Ghallabi, Fathi Essalmi, Mohamed Jemni and Kinshuk

Abstract The reuse of e-learning personalization resources has become an important topic of research in recent years. A number of learning systems in the literature allow tutors to compose and assemble the mentioned resources by reusing existing resources. However, very little research is available that focuses on optimizing the composition process. This paper presents a new approach to select the optimal composition of e-learning personalization resources. It is based on Sim-Dijkstra algorithm and composed of four layers (tutor, composition, service, and e-learning personalization resources).

Keywords Optimal composition · Quality of service · e-learning personalization resources · Web services

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36.1 Introduction

A personalized learning course consists of a set of interconnected resources. These resources can be classified as pedagogical resources and software resources. The composition methods allow tutors to generate new resources out of existing ones with minimal cost and time. These methods include composition operators and algorithm. In the literature, several approaches have used these methods in order to create new resources. For example, Duitama [1] proposed a solution which allows for reusing and composing the pedagogical resources. The composition in this approach is obtained by applying composition operators. Several works in the literature have used different composition methods to combine pedagogical and software resources according to the tutors' needs. But these works have not presented any approach for selecting the optimal composition. In addition, they have not defined the criteria for selection of the best resources.

This paper answers the following research question: *How to obtain the optimal composition of e-learning personalization resources adapted to tutors needs?* To answer this question, the paper presents an approach to improve the composition of e-learning personalization resources by selecting the optimal ones. The proposed approach is based on Sim-dijkstra algorithm [2]. This algorithm considers the resources as a collection of Web services. Then, it considers the quality of service as criterion to choose an optimal composition (path of service).

This paper is structured as follows: Sect. 36.2 presents related works and classifies them according to the type of resources (software and pedagogical). Section 36.3 describes the proposed approach. Finally, Sect. 36.4 concludes the paper with a summary of the work and futures perspectives.

36.2 Related Works

Personalized learning systems use several resources in order to create courses adapted to the learners' profiles [3]. Current emphasis on the reduction of costs of development of new resources has motivated the reuse of the e-learning personalization resources in the creation of new resources. Several works in the literature have focused on this issue. For example, Kop [4] proposed an approach which allows for combining reusable pedagogical resources and services adapted to learners' preferences. The proposed approach used Web services and algorithm to compose software and pedagogical resources. Farhat et al. [5] proposed an automated approach which allows authors to compose learning objects. The proposed system used algorithm and rules in order to generate the graph composition. Essalmi et al. [6] defined an approach that uses Web services technologies for selection of personalization parameters and to combine them in a flexible way.

Table 36.1 Pedagogical and software resources

Proposed approach	Resources	Composition criteria	Composition methods
Kop [4]	Pedagogical resources Software resources	Coherent, available	Algorithm
Farhat el al. [5]	Pedagogical resources	Coherent, available	Composition operators, algorithm
Essalmi et al. [6]	Software resources	Available, coherent	Composition operators
Essalmi et al. [7]	Software resources	Flexible	Composition operators
Jovanović [8]	Pedagogical resources	Coherent, available	Algorithm

Table 36.1 summarizes the above-mentioned approaches and shows the various resources used to provide personalized learning courses. The composition in the mentioned works is obtained by applying different composition methods. These methods are presented as follows:

– Composition operators: These operators are sequence, parallel, and alternative.
– Algorithm: This type of method allows for identifying the suitable reusable resources based on its metadata or ontology.

Furthermore, the systems reported in related works used some criteria in order to choose a suitable resource. These criteria are defined as follows:

– Coherence: This criterion allows for composing the resources in coherent way in order to build a new resource.
– Availability: This criterion allows for providing permanent software resources.
– Flexibility: This type allows for combining and composing the pedagogical and software resources in a flexible way according to the tutors' needs and the learners' profile.

To sum up, while the related works use variety of composition methods for the composition of e-learning personalization resources, none of them focuses on optimizing composition based on the criterion of quality of services (QoSs). These criteria allow for building new resources by composing the existing resources with minimal cost and time. In addition, these compositions are not based on optimization algorithms to generate optimal resources.

This paper presents an approach to enhance the composition of pedagogical and software resources. It is based on the Sim-dijkstra algorithm [2] and uses the QoS as criterion to choose an optimal composition.

36.3 Proposed Approach

The proposed approach allows combining the existing resources in order to create a new resource. Each resource is represented as a Web service. This research aims to combine the e-learning personalization resources and to find an optimal composition.

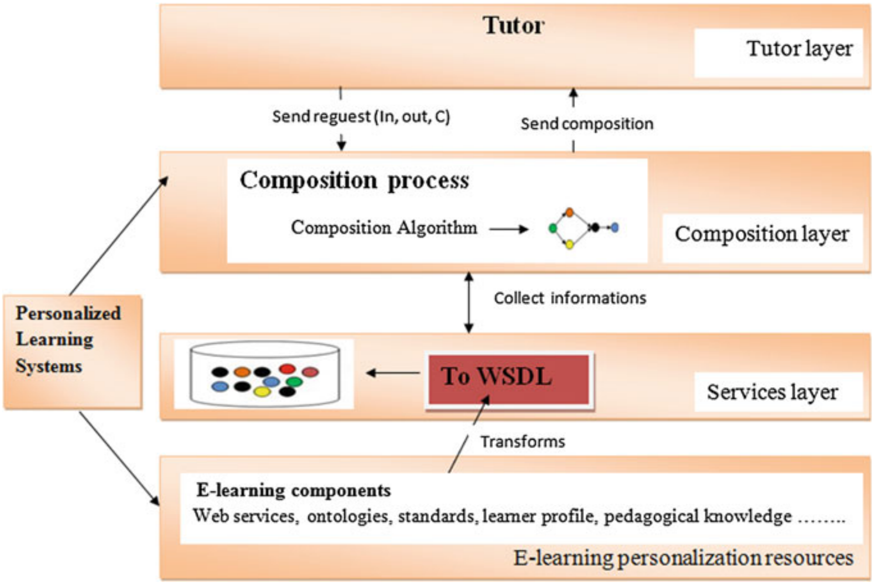

Fig. 36.1 The proposed approach

The architecture of the proposed approach is composed of four main layers (tutor, composition, service, and e-learning personalization resources) as shown in Fig. 36.1. The e-learning personalization resources layer presents various e-learning personalization resources. The service layer allows for presenting these resources as Web services by using the mechanism "TOWSDL." The tutor uses the tutor layer to write his/her request. Therefore, the composition layer which composes these resources will satisfy the tutor's request.

36.4 Conclusion

This paper presents a new approach that composes the appropriate resources according to the tutors' request. This approach is based on Sim-Dijkstra algorithm. The main advantages of this approach include providing optimal composition and responding instantly to the tutors' request. Future works will focus on implementing and validating the proposed approach (service layer and composition layer).

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Chapter 37
MOOCs in Higher Education—Flipped Classroom or a New Smart Learning Model?

Diana Andone and Radu Vasiu

Abstract This paper presents concepts and experiences of the flipped classroom method based on integrating OER and massive open online course (MOOCs) into traditional higher education in Romania. A study case on integrating MOOCs in courses at master level is presented and discussed within the flipped classroom method. MOOCs are becoming a way of responding to the actual trends in education and learning: increase in the use of online learning, delivery of shorter courses, creation of new awarding schemes, and increase of partnership in building new curricula. The new teaching opportunities and instructional challenges on integrating OER and MOOCs in technical higher education are examined from tutors and students perspectives. These activities require the acquisition of new skills by students and teachers. Advantages and limitations on using this educational model from concepts to management and technology indicate the challenges that lay ahead of educators who are willing to include MOOCs in their everyday teaching activities.

Keywords MOOCs · OER · Flipped classroom · Higher education · Blended learning

37.1 Introduction

In 2008, Siemens and Downes delivered an online course called *Connectivism and Connective Knowledge* [1] as the first massive open online course (MOOC), but the 2011–2013 xMOOCs hype was considered as a major disruption of higher education. However, since the start of the MOOCs "frenzy," major changes in education

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due to MOOCs are yet to be observed. If anything, MOOCs have enabled tutors and policy makers to start rethinking the way courses are being delivered to the students.

Several university professors [2] started using MOOCs in a successful symbiosis with their traditional course by embracing blended learning or the flipped classroom concept. Blended learning refers to a formal education program where the student learns at least some parts of the course via the online and digital medium, taking part as well, at some face-to-face classroom sessions in a "brick-and-mortar" school institution. Flipped classroom [3] is a form of blended learning in which the students usually learn the content from someplace else then the school and in the face-to-face meetings they pose questions and solve homework and practical activities.

37.2 MOOCs in Traditional Education: The Flipped Classroom Model

The "flipping" classroom is a concept which starts again to be especially appealing to higher education. As a concept, this model puts the student in control of their learning and has countless advantages but also some challenges for implementation.

It is considered that having the time and space to investigate, communicate, and produce creative projects within a flipped classroom can only help set students to be successful [3]. This idea of giving students more opportunities to work collectively is certainly engaging and relates with the new methods of teaching STEM subjects or in engineering education. Flipped classrooms offer a powerful opportunity for embracing new technologies and the new educational methods as MOOCs. A blended learning model can be achieved by mixing the MOOCs technology with traditional class, by taking the MOOCs from the large scale and applying them to small-scale courses [4]. Several methods of integration are used at this moment in different universities [3, 5], and some have been integrated based on a cMOOC (connectivist) concept [6]. There are several ways in which MOOCs can be blended in higher education courses mainly based on the following: the topic complementarity with the course, the synchronicity between the MOOCs and course, and the numbers of MOOC to be integrated.

37.3 UPT Study Case

In Politehnica University of Timisoara (UPT), there were several pilots on integrating MOOCs in traditional courses [5] and in the assessment and evaluation of student coursework based on this, as well as in the integration of open educational resources (OERs) as external resources [5, 7]. One UPT study case involved Master of Science students' in the instructional technologies course where MOOCs were used as external resources to the course in the Autumn 2014. As this course is part of a traditional face-to-face specialization with predetermined curricula, the course syllabus needed to be adjusted as to allow the students' MOOCs activities to be recognized as learning outcomes. The instructional model of this course is based on the flipped mode classroom with the tutor indicated the course target and activity objectives, combined with the integration of OERs. The students' activity consisted in analysis of online learning environments, the connection between the instructional model used in different online learning environments, the different tools integrated in courses, and the impact of interactive media materials (videos, animation, etc.) have over learning. To achieve this learning target, the students needed to attend courses on different online learning environments (in this case MOOCs), to compare and analyses the different educational technologies used, as part of their practical activities, and to produce a final report. The activity finalized with an instructional technologies report and in class debate which consisted as 25 % of their final mark. The 27 students involved took 16 courses (45 % edX, 34 % Coursera, 5 % FutureLearn, 5 % iVersity, Udacity, but also some not as popular as Open2Study, duolingo, open2study, nu, Saylor, gymnasium.aquent.com) on subjects related to technologies. As to evaluate this study, the tutors applied an online anonymous survey and interviews. The results revealed that 25 students finalized the MOOCs to which they subscribed, the rest using the materials only as references. It is also worth mentioning that 87 % of students attended a MOOCs before so they were familiar with them and 73 % accessed the courses also from their mobile devices. 57 % of students considered activities in MOOCs as normal higher education activities and of similar information quality as their everyday courses. An interesting aspect during this pilot was the continuous critical discussion between the students and the teacher regarding the quality of the video materials, the instructional methods used in different courses, the course interaction between peers, and the evaluation and assessment methods. Some of this discussion was held online in the dedicated blog on CVUPT (the university Virtual Campus), and some was during the face-to-face classes. MOOCs weaknesses were indicated by the students also during survey as results to the question where students were asked what they disliked more in attending the MOOC: 48 % indicate that is the lack of direct communication with peers, followed by no communication with tutor, some (20 %) indicate to many external resources to follow but also that "it was to easy and not helping me." Figure 37.1 presents the tools and activities students will prefer to be included in MOOCs.

Some stirring comments in the blog were related to students reported the need for a direct communication and feedback from MOOCs facilitators, not only from peers as a more valuable and qualitative feedback and as a personalization of learning. Some students reported that in MOOCs, the students should have the possibility to choose which of the learning pedagogies they want to follow.

A wiki tool, in CVUPT, was used by students to create or contribute with course content, which they assessed as relevant to the specific topics indicated by the teacher. The topic with the most comments and references was related to course structure, students concluding that "in order to have quality content, the teachers and course material creators should have access to a number of powerful and

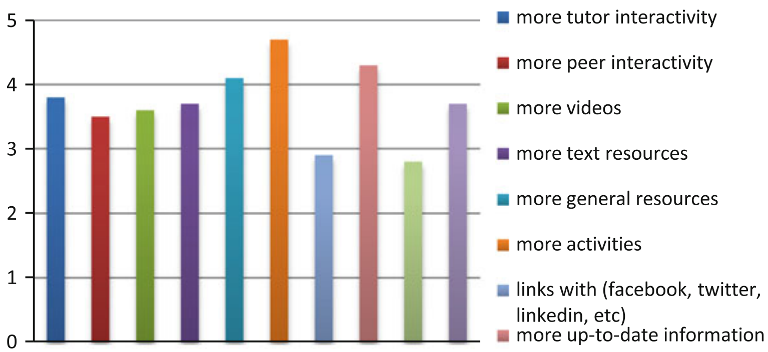

Fig. 37.1 MOOCs needed activities and tools as indicated by students

intuitive tools for content editing and structuring," and this might increase the participation retention in a MOOC. Students indicated that a clearer, more specific assessment during the final evaluation of a MOOC is needed as to encourage participants finalizing the course.

Students reported a high interest in MOOCs and in the educational model it provides, declaring their willingness to take part in future MOOCs activities, as part of their lifelong learning strategy, and some indicating that it might be their preferred method for personal development. This case study proposes a new method for open educational practices, bringing new perspectives for integrating MOOCs in blended courses/flipped classrooms. Students have had a high autonomy in assessing their own learning needs for choosing the MOOCs in which to participate in order to deepen the course topics, but also to find useful information for group project development (another activity where they needed to design an online course).

37.4 Conclusions

New skills and tasks are required for teachers facilitating blended courses integrating MOOCs: complex course design and management, OERs, and MOOCs. All of these could be accomplished only if teachers adopt a new and open attitude toward the teaching–learning process, have the will to test and to learn new things together with their students, and wanting to oppose uniformity and self-sufficiency.

We consider that in today's world, it can be beneficial for every university to at least try the MOOCs experience, from a user experience, and for any higher education academic, it can be a different experience. For Romanian universities, which are public funded and where online learning is nor encouraged or recognized, the involvement on integrating MOOCs in a higher education environment is mainly backed by their belief that valuable knowledge and information need to be made available to the students, new methods of teaching and instruction need to be used, and students need to be fully encouraged to discover and develop skills for online and lifelong learning.

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Chapter 38
Enhancing Employability Through e-Learning Communities: From Myth to Reality

Maria-Iuliana Dascalu, Bianca Tesila and Raluca Andreea Nedelcu

Abstract The paper presents a tool which can be used to prove the correlation between social learning and employability. The tool aims to facilitate adults' leap toward a better professional life and gives them the opportunity to find meaningful professional e-communities, in which they can learn from their peers. In the same time, during learning within platform communities, users' professional visibility is enhanced, as exceptional behavior within those communities is rewarded by recommending them to job recruiters who seek competent workers. The proposed learning instrument is highly suitable for today's social and cultural values and is based on latest technologies: semantic Web, recommender agents, ontologies, and social network connectors.

Keywords e-learning communities · Social learning · Ontology · Employability

38.1 Introduction

As a follow-up of the technological opportunities, today's cultural and social values have changed. Online education is seen as the next educational bubble, capable of exceeding the importance of higher education, when considering only the skill sets developed during the learning process and not the reputation given by a well-recognized study diploma [1]. In the same time, online education is preferred by knowledge workers, who are involved in self-directed continuous professional

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development [2], equipped with IT culture, highly active in e-communities, and always ready for a more challenging job position [3]. The efficiency of learning, in their case, is not measured in grades, but in progress toward personal goals and gains in income or employment [4]. Also, they tend to consider a consolidated profile on social networks to be more efficient than traditional forms of learning, with respect to job searching and, consequently, becoming employed [5].

As a consequence of these society changes, we propose an electronic platform, EmployLeaP, which will foster lifelong learning through facilitating the access of knowledge workers to suitable e-learning communities. The learning platform uses recent semantic and social Web technologies, and it will help its users to make a leap toward the status of being employed, as the users have the possibility of being recommended to job recruiters and organizations based on their virtual behavior.

This paper presents the main functional and technological characteristics of the platform, in the context of employability and social e-learning. Even more, it demonstrates that the correlation between being engaged in learning activities and becoming employed is straightforward in the case of EmployLeaP and not just an overrated belief or a myth.

38.2 Employability and Social e-Learning

Employability means "the individual capability to gain employment, to maintain employment, or to replace an employment relationship by another, if necessary or wanted" [6]. There are studies which underline the connection between the features of being employable and learning [4, 6]. Nevertheless, there is no platform which can effectively support learners to search for the most suitable job while being active in an e-learning environment: Some of them support either online learning (e.g., Stackoverflow, Khan Academy European Civil Society Platform on Lifelong Learning EUCIS-LLL, VSTAR), or job seeking (e.g., LinkedIn). EmployLeaP provides, in the same time and place, opportunities for improving oneself through learning from the others and being hired.

Nowadays, a central driver in e-learning is collaboration. Learning from one's peers increases the engagement in the learning process and also the retention rate of new concepts [7]. Collaboration is encouraged through several Web tools and technologies: social media, forums, wikis, chat rooms, blogs, or virtual worlds [8–11]. Social networking sites are seen as ubiquitous learning environments, while online communities of practice successfully promote the concept of "learning by teaching" [7]. EmployLeaP combines several semantic Web technologies and exploits existent social network APIs in order to provide a highly collaborative ICT service for knowledge workers to learn and become visible to employers and their peers.

38.3 Social Learning Platform to Increase Employability—Functionalities and Technologies

Functionalities. EmployLeaP is a Web platform for self-built communities that facilitate the process of lifelong learning by engaging interested users into a continuous educational process: These users can share and gain knowledge with respect to a particular interest, while increasing their visibility to professional recruiters who are registered in the environment. The access to a community is facilitated by the platform through an ontology-based recommendation algorithm—when a learner registers to EmployLeaP through a social network account, all his/her skills and current job position are parsed and processed and an individual with the same properties is added to the ontology. This also applies to the use case of a recruiter—EmployLeaP retrieves the job position and the domain of activity. The EmployLeaP ontology contains properties and relationships that are used to establish user interests—they are the main driver for obtaining existent communities that are suitable for a particular user.

The learners' profiles are accurately built, without consuming too much time, as connectors to most used social networks were developed (for the moment, LinkedIn and Facebook).When a user logs in for the first time, EmployLeaP displays all the recommended communities for his/her interests (based on one's profile)—from this moment, the learner has the choice of enrolling in a community, while a recruiter can follow a community. Each such e-learning community is presented through the medium of a forum, where interested "community seekers" can post questions or answers with regard to a specific topic on the community's main subject. The recruiters can only visualize the discussion threads within followed communities. By actively participating in a forum and helping one's peers with relevant information, a learner gains points through votes given by other learners. Moreover, even the action of posting a question or an answer is awarded with an amount of points, this also outlines the fact that the learner is active within a particular community. Every community seeker can keep track of the communities in which he/she has enrolled, along with the accumulated scores with respect to them.

Moreover, in order to keep learners motivated, a gamification principle is applied—taking into account the amount of points, a user is labeled with a corresponding badge and can be visible through the top users of a specific community. Apart from gaining popularity among other community seekers, a user becomes more visible to job recruiters that are following the same e-learning communities, seeking valuable or potential professionals interested in a particular subject. Recruiters can get in touch with the most appreciated members of a community.

Technologies. Several technologies have been used to develop the Web multi-tiered application platform: Java EE, Spring, Apache Tomcat, Hibernate Framework, MySQL Community Server. As far as the ontology integration is concerned, EmployLeaP easily makes use of predefined ontologies by implementing functionality through the medium of OWL API—Java API for creating, manipulating, and serializing OWL ontologies. The platform can retrieve individuals' information related to defined classes and object properties in order to perform the previously mentioned recommendation algorithm. In addition to this, the platform can dynamically update the used ontology with new information in order to adapt to new registered users and their interests, also by using OWL API.

38.4 Conclusions and Future Directions

EmployLeaP platform personalizes the educational experience of each learner, by recommending communities with similar profiles, while increasing one's employability through facilitating the connection to recruiters that are looking for such profiles. The provided functionalities are recruiter specific, learner specific, and global specific, so the platform will be a useful tool for organizations, also. The platform was tested in a controlled environment, but encouraging results were obtained. We think it will be a valuable instrument to prove the connection between meaningful social e-learning and being employed, when it is used on large scale. As future directions, we plan to improve the recommendation algorithm, by making the platform ontology more flexible and also, continuous work regarding social connectors is necessary.

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Chapter 39
Performance Augmentation Through Ubiquitous and Adaptive Learning and Work Environments

Erik Isaksson, Ambjörn Naeve and Paul Lefrère

Abstract Recent and upcoming devices such as tablets and wearables in combination with technologies such as the Internet of Things are resulting in learning environments becoming of an increasingly ubiquitous nature. Learning environments are now more strongly embedded in real-world learning and work activities, causing the boundaries between virtual learning environments and their real-world contexts of use, and between learning and work activities themselves, to be increasingly blurred. A reconceptualization of learning environments as performance augmentation means that the function of enhancement or augmentation is made explicit. Theoretical, modeling, and implementation aspects of performance augmentation through ubiquitous and adaptive learning and work environments are explored.

Keywords Learning environments · PLEs · Activity theory · Linked data

39.1 Introduction

Recent and upcoming devices such as tablets and wearables (smart glasses, trackers, watches, etc.) in combination with new technologies such as the Internet of Things are resulting in learning environments becoming of an increasingly ubiquitous nature. Whereas learning environments such as virtual learning environments (VLEs) and personal learning environments (PLEs) could previously be regarded as

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exclusively digital in their contexts of use, often on personal computers (PCs) in non-work settings, learning environments are now, through a variety of new devices and technologies, more strongly embedded in real-world learning and work activities. Thus, the boundaries between virtual learning environments and their real-world contexts of use are becoming increasingly blurred, as are the boundaries between learning and work activities themselves.

A reconceptualization of learning environments as performance augmentation means that the function of enhancement or augmentation is made explicit. At the same time, the emphasis on a possibly specific *environment* for *learning* is substituted in favor of an implicit ubiquity, i.e., any and every environment, and adaptability, i.e., performance of any kind of activity, whether learning, work, or likely both as any activity involves learning on some level.

This reflection paper explores some theoretical, modeling, and implementation aspects of performance augmentation through ubiquitous and adaptive learning and work environments.

39.2 Learning and Work Environments

A *learning environment* “refers to the diverse physical locations, contexts, and cultures in which students learn. Since students may learn in a wide variety of settings, such as outside-of-school locations and outdoor environments, the term is often used as a more accurate or preferred alternative to classroom, which has more limited and traditional connotations—a room with rows of desks and a chalkboard, for example” [1]. Whereas a VLE or PLE would likely be regarded as being separate from its wider educational or work context, for the purposes of performance augmentation, they are to be regarded as semantically one and the same. That is, the contextual learning and work environment such as a course or workplace *is* the learning and work environment, which is then augmented, but not replaced, by virtual and possibly personal or collaborative counterparts. Reversely, even a real (physical) environment such as a classroom or factory floor could be regarded as a, possibly temporary, augmentation of the actual learning and work environments, e.g., a course for which one session is held in a particular classroom.

This definition of learning and work environments brings it closer to that of “activity” in activity theory. There, *activity* “refers to a special type of relationship between a subject and an object (as in ‘objective’), characterized by two distinctive features: (a) subjects of activities have needs, which should be met through subjects’ interaction with the world, and (b) activities and the entities they are relating (i.e., subjects and objects) mutually determine one another. More generally, activities are generative forces that transform both subjects and objects” [2]. For example, in a course, mainly the subjects themselves (students) are transformed toward an objective (the learning goals), whereas in a workplace, both the subjects (workers) and objects (the products or services) are transformed, through learning by experience.

39.3 Performance Augmentation

Vygotsky [3] introduces the *zone of proximal development* (ZPD), being the difference between what a learner is capable of doing unaided and what he or she can do when she has aid, e.g., of a teacher. Similar to the aid of a teacher, performance augmentation aids a subject to be able of doing more than he or she would have been able to do otherwise and also to learn and hence able to do more both unaided and aided in the future.

Performance augmentation, or more precisely the devices through which it is mediated, is in activity theory terms regarded as a special kind of tool, namely a *functional organ*. Leontiev [4] introduces the idea of functional organs as "created by individuals through the combination of both internal and external resources": "Functional organs combine natural human capabilities with artifacts to allow the individual to attain goals that could not be attained otherwise. For instance, human eyes in combination with eyeglasses, binoculars, microscopes, or night vision devices, constitute functional organs of vision that may significantly extend human abilities" (quoted from [2]).

Human–computer interaction uses the terms *gulf of execution* and *gulf of evaluation*. Norman [5] describes the gulfs simply: "When people encounter a device, they face two gulfs: the Gulf of Execution, where they try to figure out how to use it, and the Gulf of Evaluation, where they try to figure out what state it is in and whether their actions got them to their goal." The gulf of execution is "bridged by making the commands and mechanisms of the system match the thoughts and goals of the user," whereas the gulf of evaluation is "bridged by making the output displays present a good conceptual model of the system that is readily perceived, interpreted, and evaluated," both with the goal "to minimize cognitive effort" [6].

Performance augmentation is meant to apply to learning and work activities in their entirety, and therefore, the gulfs to be bridged encompass those of the totality of those activities. For example, for a factory worker to complete her task from start to finish, the gulfs include how to use the factory to carry out the task (execution) and the state of the factory and everything therein (evaluation).

39.4 Modeling and Implementation

Whereas an appliance, such as a piece of machinery, typically has a single function, tablets and other modern, "smart" devices are universal and able to become, or implement, a specific "appliance" by means of "apps." These can be regarded as tools for performance augmentation.

However, current devices and app platforms are lacking a shared semantic model for sharing resources across devices and apps and placing them in their contextual (learning and work) environments. Instead, it ought to be possible to mix and match appropriate apps for "bridging the gulfs" for each environment and person, depending on the tasks to be carried out and the specific needs and preferences of that person, while still interacting within the same contextual environment. Potentially, there is more than one contextual environment, such as a course, oneself (a personal environment), and the physical classroom, and it ought to be possible to access all of these simultaneously with their resources in effect merged.

The main approach taken in our work is based on Linked Data, which is a method of publishing structured data on the Web according to standards, using data that is self-descriptive (i.e., with embedded semantics), thus making it possible to look up information about anything using only its identifier and to link anything to anything, similar to hyperlinks on Web pages. Linked Data is not limited to identifying and providing information for digital things such as various electronic learning resources, but works equally well for real (physical) and even abstract concepts. Because of a shared meta-model, it is possible to merge information from multiple sources. Therefore, Linked Data is advantageously positioned for supporting a step from digital (or traditionally virtual) environments such as VLEs to hybrids of real and virtual ones. A particularly important case is that of learning by experience, e.g., on a factory floor using state-of-the-art and upcoming devices for augmented and virtual reality (AR and VR), where the Internet of Things and a model based on Linked Data together with appropriate ontologies can function as a bridge between the real and virtual.

39.5 Conclusion

The end goal of performance augmentation through ubiquitous and adaptive learning and work environments is precisely that performance augmentation indeed may become ubiquitous and adaptive with optimizable, smart learning and work environments that are capable of being adapted to learner and worker needs and preferences. Standardization such as Linked Data and shared semantic models to support specialized apps in any environment are important steps toward this.

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Chapter 40
Peer Review from Teachers' Perspective

Comparing Five E-Business Learning Scenarios in Higher Education

Michael A. Herzog and Elisabeth Katzlinger

Abstract Peer review, a well-known method for quality assurance in science, is now being used as a teaching method in universities. In this work, we present an analysis of five different teaching scenarios that use peer review as the main method. All scenarios use the same technical setting within different courses in e-business education and include approximately 600 participants. Qualitative and quantitative data from over 300 students were collected and analyzed. When used for more laborious, elaborate, complex, and cognitively ambitious assignments, similar to writing academic papers, peer review tends to be less liked by inexperienced students. For well-structured, less time-consuming tasks such as management process modeling exercise, peer review is better accepted and higher rated even in settings with much larger groups. Further analysis of more than 30 criteria such as lead time, support expense, tutoring suitability, conflict potential, dimension of cognitive processes, meeting professional standards, self-motivation, and social interaction could show how the five different peer review scenarios lead to either better or less efficient learning performances.

Keywords Peer review · Peer assessment · Learning scenarios · Educational method · Scientific learning · Self-directed learning · Higher education

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40.1 Introduction

In the academic world, peer review is regarded as a suitable method of quality assurance and evaluation. Researchers of similar competence review and comment on papers of their peers. Peer review is also increasingly used as a learning method particularly in the university contexts where competence acquisition and active, student-centered methods tend to complement or replace conventional methods. A peer review method is easily integrated into learning arrangements that place special emphases on self-regulated and experience-oriented learning. In order to review a paper, reviewers must acquaint themselves thoroughly with its topic which will also enhance their own understanding. Peer review as a learning method draws on learners' knowledge and expertise from their different work experiences and fields of study. Part-time students especially often can exploit knowledge from their work experiences in their peer reviews.

Furthermore, since peer review can be done independently and autonomously, it accommodates many student scheduling constraints. It also integrates collaborative learning as peer comments and reviews provide useful feedback. Moreover, it triggers the formative promotion of mutual support groups among learners. From a teacher's perspective, peer review can be beneficial since it is suitable for large classes and is easily scalable [7], many submissions lead to many reviewers.[1]

Just as a wide range of pedagogical tools and instructions exist for many well-established learning and teaching formats, peer review is frequently described in the literature, especially since the 1970s. Surprisingly, it has seldom been investigated for its concrete applicability as an instrument for different teaching tasks and assessment [5]. A literature review by Van Zundert et al. [9] shows that few empirical studies examine how peer assessments might be best utilized for learning. This gap is more significant since many capable tools for the organization and utilization of peer reviews have been developed particularly during the past five years. Thus, the effort required from teachers has decreased and the instrument is more easily available for broader use. This provides new opportunities for the use of peer review with other learning approaches especially in connection with student-centered methods.[2]

In this study, teachers from two different universities, in Germany and Austria, investigated the use of five different learning scenarios that incorporate peer review as an essential learning method. It includes experiences from 17 courses with a total of 600 participants. These scenarios are compared by the use of a criteria analysis and related to results of an accompanying online study in order to determine the advantages and disadvantages as well as recommendations concerning practical

[1]The wide range of further advantages and application possibilities is summarized in [8] on page 11 which also comprises a broad literature review on the subject.

[2]A good example for a combination possibility of peer review with constructivist methods is described in the Expertiza approach where students develop small-scale learning materials for use by their colleagues which can be improved by peer reviews [2].

application of peer review. At this point, data from three of the five scenarios, gathered by an online survey of 304 participants, are examined.

40.2 Learning Scenarios

In this section, the five different learning scenarios that use peer review as a learning method are described (Table 40.1). The organizational tool used is the activity "Workshop" of the learning management system Moodle. This workshop activity consists of four sequential phases (preparation, submission, evaluation, and assessment) that are initiated and actively accompanied by teachers. Thus, for example, assessment points can be revised if one of the reviewers provides an unfair assessment. Reviewers assess their peers on basis of rating sheets that contain a diversity of assessment criteria.

Individual criteria are rated by the use of numeric points. Additionally, individual criteria can be weighted differently. Furthermore, each criterion should be commented on by means of a short verbal statement that should contain the reviewer's reasons for his or her evaluation. During student training, it was

Table 40.1 Learning scenario overview and basic data of survey (gray columns)

	Scientific paper writing	Abstract writing	Case study reporting	Process model creation	Exercise editing
Number of participants in each course	6…16	26	22…24	40…130	15…40
Number of courses (2013-2015)	3	1	3	5	5
N in survey	-	-	54	155	95
Study progress / semester (1…12)	10	8	9	3	4
Individual work	x	x	x	x	x
Group work	one course	-	-	one course	-
Structure of task	un-structured	un-structured	semi-structured	pre-structured	semi-structured

important to draw students' attention to the possibility of verbal feedback since it offers great learning opportunities.

40.2.1 Scientific Paper Writing

Similar to the peer review process at academic conferences, students prepare a scientific article and submit it. In this research-based teaching scenario at the Masters' level, peer review is applied as one of several possibilities for providing feedback within an iterative, self-directed learning process (Fig. 40.1) [4].

Since this learning situation tends to become very complex because of intensive feedback and the individual supervision and support needed, only one course was conducted in group work, in order that this method could be applied for larger groups of students. We underestimated the challenges in assigning reviews, motivating the process, and managing conflicts as shown later.

40.2.2 Peer Review of Abstracts with the Possibility of Revision

Within this learning scenario from an e-business seminar in a masters' program, Digital Business Management, students were assigned to the task of defining a subject for their seminar paper and writing an abstract for it. The topic of the seminar was "sharing economy" [6] and its characteristics. Students received guidelines on the structure of the paper that included information on what should be covered. They finally submitted a two-page abstract for the review.

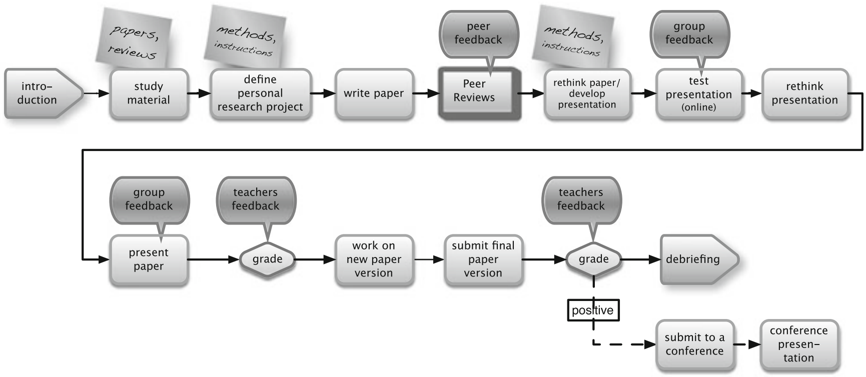

Fig. 40.1 Research-based learning scenario with peer review (Scientific paper writing)

Each student was assigned three abstracts to review. For assessment, reviewers were provided an evaluation grid from one to ten points but the main focus was on verbal feedback. This was used by all reviewers. Subsequently, students had the opportunity to revise their abstract based on suggestions from reviewers. Revised and updated abstracts were presented to the seminar group and compiled to a seminar program of content-related sessions.

40.2.3 Peer Review of Case Studies

In the class "IT Ethics" in the masters' program in Digital Business Management, students deal with a case study on computer ethics. They independently choose one case study from the compilation book "remorse" by Weber-Wulff et al. [10]. The case study is developed in writing and submitted anonymously. Students organize their draft based on an analysis grid in order to make sure that they work on the ethical issues and problems methodically as well as systematically. Reviewers evaluate those drafts by means of an analysis grid and give verbal feedback mainly focusing on whether the argumentation regarding the case studies is logical and comprehensible. In this scenario, the reviewers benefit not only from the work on their own case studies but also from their peers' approaches to their own cases and the solutions they developed.

40.2.4 Peer Review of Models

For bachelors' courses with more than 50 participants, an alternative approach needed to manage courses requiring significant support efforts. Students of business engineering received the task of gathering information about a modeling technique in the field of business process management and employing it in a standardized case of application. The developed process models (mostly one to three pages) were submitted to peer review and evaluated by two or three other students according to review criteria that were specially created for this modeling. There was an attempt to use the advantages of group work within larger classes during a pilot semester. To limit the efforts of guiding large groups, in following courses, e-tutors were involved providing additional feedback in peer reviews.

40.2.5 Peer Review of Exercise Examples

In the course "Business and Internet," an introductory course for bachelor students of economic sciences, students received a short task description on e-procurement. In this task, various goods need to be purchased. Students choose a suitable classification method and corresponding acquisition methods for the various goods and base the reasons for their choices using the background theory of this course. The reviewers evaluated different criteria and especially the reasons for choices as well as their argumentations.

40.3 Comparison of Different Learning Scenarios

The use of peer review opens up a whole new range of design possibilities which is why the aim was to create already improved learning situations during the courses of this study. This is the reason why model creation task and e-procurement exercise with large- or medium-sized groups of students in second or third year of their bachelor's degree were rather focused on one specific subject. Scientifically more challenging learning scenarios, such as paper and abstract writing, as well as the case study on IT ethics are addressed in smaller groups of master's students requiring a high level of support.

Figure 40.2 shows different dimensions of learning scenarios and gives an estimate by teachers of the characteristics of tasks underlying the peer review. Tasks differ not only in their degree of structure and their associated complexity, but also in their cognitive challenges.[3] Less pre-structured tasks—in this study scientific paper writing and abstract writing—demand either a high level of methodological and subject-specific knowledge from students or intensive and often individual support from teachers. Well-structured tasks on clearly limited subject matters—such as the exercise and model tasks—are suitable for larger groups of beginning undergraduates.

These surprising differences between individual tasks are also reflected in the learning effects expected by teachers: complex, cognitively, methodologically, and scientifically more challenging tasks should achieve higher learning effectiveness in peer review, too, which can only be seen in connection with corresponding tasks.

40.3.1 Support Efforts and Benefits

Time efforts of teachers during peer review strongly vary from scenario to scenario, depending on the given task (Table 40.2). Exercise editing and model creation requires a review of most feedback by teachers, especially in case of varying results. The review of abstracts and case studies was announced and completed as mere peer activities on the part of the students without any intervention by teachers.

[3]Dimension of cognitive processes was rated using the six-step taxonomy of Anderson et al. [1]. For comparing reasons in our context, the scale was adjusted to 1 … 4.

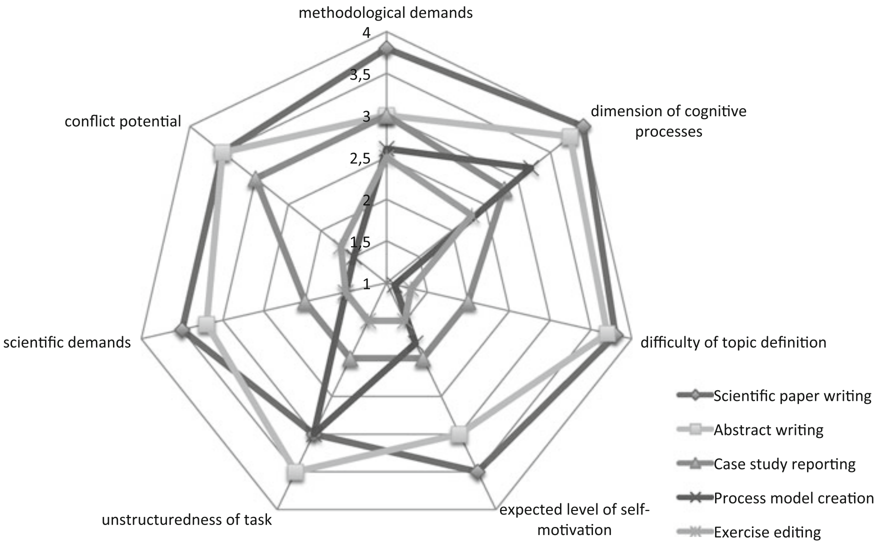

Fig. 40.2 Individual teachers' rating from 5 learning scenarios (No empirical data! Scale from 1 = low to 4 = high)

Table 40.2 Individual teachers' time expectations for the five learning scenarios

	Scientific paper writing	Abstract writing	Case-study reporting	Process model creation	Exercise editing
Desired time span of task for students (~ in hours)	120	20	16	16	8
Desired time span of reviews (~ in hours)	8	3	4	3	3
Number of expected peer reviews	2	3	3	2	2 … 3
Support effort for peer review/student (~ in hours)	1.8	0	0	0.2 (tutor supported)	0.5
Evaluation of learning effects by teachers, scale 1 = low … 4 = high	3.8	3	2.5	3	2

In order that peer review can be successfully completed by students without further supervision by teachers, a meticulous planning and preparation of the task description as well as a perfect technical and content-related implementation of the preparatory work on peer review platform are critical for success. The scenarios' abstracts and case studies additionally require high support in the follow-ups of reviews. The particularly high support effort required by peer review of papers was due to the length of the papers which are between nine and 20 pages, and on the quality of the peer feedback. In the process model scenario with large groups, teachers revised submitted models and all of their reviews. Due to the very clear assessment criteria and good examples, in a second step this task could be easily delegated to tutors, who were identifiable as such in the learning platform. Students readily accepted the tutors' assessments and the conflict potential was quite low.

As frequently mentioned in the literature, here, too, dealing with different papers at the same level and learning from mistakes were mentioned as the main learning benefits from the scenarios investigated. This benefit, as well as student satisfaction, could be considerably increased if a second submission were graded. However, a second submission requires more feedback and an increased workload for teachers.

40.3.2 Student Evaluation of Learning Scenarios

Students participating in the scenarios case study, model, and exercise were asked in an online questionnaire about the benefits of peer reviews (Fig. 40.3). On a four-point Likert scale, peer review as a learning method was positively rated in all criteria. Former investigations [3] already show that peer review as a learning method surprisingly compares favorably with other learning scenarios (e.g., game-based learning) from the students' perspective. The model creation task was rated best in all categories, whereas the peer review of the case study got the worst

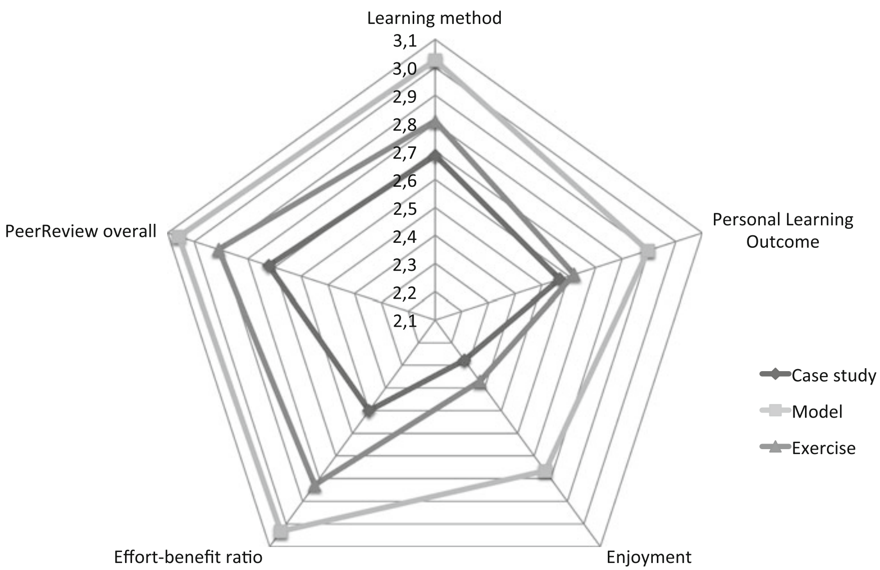

Fig. 40.3 Student evaluation of peer review (n = 304); scale 1 = poor … 4 = excellent

rates here. Review on case study was conducted in three different terms, whereby one of the three courses was rated considerably poorer in all categories (the mean score is 0.5 points lower). Thus, external factors, such as group atmosphere and dynamics, can have a significant impact on the student assessment of learning methods.

The high level of satisfaction with the review of models is certainly explainable by the clear definition of assessment criteria, the brevity of the submitted work (1, 2 pages), and their evaluation as well as the involvement of teachers and tutors in the assessment process. In qualitative feedback students often referred to a lack of knowledge of their peers as being a hindrance in connection with this scenario, although they rated peer review generally positively as a learning tool.

40.3.3 Instruction, Support, and Organization of Peer Reviews

All peer reviews described in this study were conducted by means of the activity "Workshop" on the different version of the learning platform Moodle. The implementation of the Moodle activity demands a meticulous planning and strict adherence to the different steps of the process by teachers (see Table 40.3). In newer versions, it became possible to assign each review individually which makes the arrangement for group assignment more manageable (Sect. 1.1).

Giving students detailed information on peer review, its procedure and especially the assessment criteria are crucial preconditions for the success of this learning activity. An increasing level of satisfaction over the past four years in this study of students as well as of teachers shows that continuing improvement of instructions and examples, improved technical and organizational framework as well as more teaching experience could lead to better learning satisfaction for students with the use of peer reviews.[4]

Students evaluated the influence of assessments from peer review on the overall grade quite differently, as becomes obvious from the qualitative feedback. As it turned out, the feedback of reviewers was more complex and sophisticated. It was striking that whether the assessment competency of peers was doubted or not, depended both on the task itself and the student's academic progress. In such cases, students requested intervention of teachers. As students occasionally lack the professional background for good, fair, and constructive assessments, conflicts may occur which require the intervention of teachers. This effect could be prevented if

[4]Examples for briefings and assessment categories and criteria are available on the authors' Web site. Especially an overview document which describes the whole peer review process and is provided within the framework of a short introduction in the lecture already before students start the peer review module of the learning platform for the first time, has proven to be useful (Briefing).

Table 40.3 How peer review points influence grading

	Scientific paper writing	Abstract writing	Case-study reporting	Process model creation	Exercise editing
Updating possibility (revised version is graded)	Y	Y	N	N (bonus system)	N
Students review gets into grade	N	Y	Y	Y	Y
Rating of review gets into grade	N	Y	Y	N	Y
Participation of teachers/tutors in peer review	Y	N	N	Y	Y

the submitted works were reviewed more than twice. Thus, it is recommended to plan for three or four reviews per paper for the learning scenarios investigated.

Particularly getting the opportunity to revise and update one's own paper after receiving a peer review and before being graded is perceived as improving learning by students as well as by teachers. Much has been written already about the problem of how to secure anonymity in peer review process in small classes. This problem played also an important role in the quantitative feedback in this study. Getting the chance to revise and update one's own paper and being guaranteed a final grading by teachers helped with this. But also the declaration of good reviews as bonus achievements could defuse the resulting conflict potential. Yet, conflicts can also trigger productive reflection processes which contribute to the learning process.

40.4 Conclusion

Due to the use of different tasks and learning scenarios, peer review has a far wider range of application possibilities than is commonly expected. It allows for the achievement of highly different cognitive learning levels, as well as a high-level assessment competency. A differentiation according to target group and learning level is necessary—in this context, a "one size fits all" approach is neither sensible nor useful. The inclusion of learners into the learning process causes an active participation and, as a consequence, enhances the learners' motivation. Regarding learning success and evaluation by learners, peer review compares favorably with other media-based learning scenarios.

Complex, comprehensive study tasks turn out to require a considerably higher level of support on the part of teachers, as well as smaller groups in the settings described. For larger groups, well-structured, small-scale tasks have proven useful; whereby especially reviews of similar tasks can be handled quickly and the teachers' workload per student seems to decrease with each additional participant.

At this point, tutors can be easily involved and carry out some of the assessments independently on the basis of sample reviews (e.g., from previous terms). It is, however, important to remember that the peer review process itself requires intensive supervision and support by teachers even if no direct involvement in the actual review is necessary.

Particularly meticulous preparatory work including clear work instructions and task descriptions are necessary preconditions for the success of peer review as a learning method, which can be best achieved by means of an additional briefing to increase assessment competency and enhance communication. Even with advanced peer review tools, vague or incomplete work instructions lead to an abundance of queries, frustration, and conflicts on the part of students. Especially in smaller courses, teachers should be prepared for stronger group dynamics and make use of this effect for higher learning outcomes.

This study describes the application of peer reviews utilizing modern support tools and on the basis of empirical data and demonstrates its wide range of scientifically backed application possibilities. But further research is needed in the area of cognitively more challenging, more complex learning situations before utilizing these kinds of scenarios in larger groups.

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Chapter 41
Metrics for Automated Review Classification: What Review Data Show

Ravi K. Yadav and Edward F. Gehringer

Abstract Peer review is only effective if reviews are of high quality. In a large class, it is unrealistic for the course staff to evaluate all reviews, so a scalable assessment mechanism is needed. In an automated system, several metrics can be calculated for each review. One of these metrics is volume, which is simply the number of distinct words used in the review. Another is tone, which can be positive (e.g., praise), negative (e.g., disapproval), or neutral. A third is content, which we divide into three subtypes: summative, advisory, and problem detection. These metrics can be used to rate reviews, either singly or in combination. This paper compares the automated metrics for hundreds of reviews from the Expertiza system with scores manually assigned by the course staff. Almost all of the automatic metrics are positively correlated with manually assigned scores, but many of the correlations are weak. Another issue is how the review rubric influences review content. A more detailed rubric draws the reviewer's attention to more characteristics of an author's work. But ultimately, the author will benefit most from advisory or problem detection review text. And filling out a long rubric may distract the reviewer from providing textual feedback to the author. The data fail to show clear evidence that this effect occurs.

Keywords Peer review systems · Rubrics · Automated metareviewing

41.1 Introduction

Users of peer review systems have a vested interest in high-quality reviewing. Students learn from both writing and receiving reviews. As a reviewer, a student learns more by delving deeply into the author's work and composing constructive

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criticism. As a review, an author wants to see feedback that is thoughtful and offers helpful advice for improving the work. But good reviewing is an art, and our experience demonstrates that students need to be taught to write careful reviews. Ideally, students would receive feedback on their reviewing just like peer review gives them feedback on their authoring. But, as there are many more reviews than there are works to review, no course staff has the time to give feedback on all reviews.

As part of our Expertiza project [1], we have designed an automated metareview system [2, 3] that can give a reviewer feedback on a review that (s)he is about to submit. Previous work [3] relates the outcomes of user studies on a small number of reviews from this software. This paper does not consider how students interact with the review system, but instead applies the metrics from the automated metareview system to hundreds or thousands of reviews from past classes. We report on three metrics for reviews:

- Volume, which is the number of distinct words used in the review
- Tone, which measures whether a review is more positive or negative about the work being reviewed
- Content, which classifies textual feedback within a review into one of the three categories
  - Summative, which says that some aspect of the work is good or bad
  - Problem detection, which identifies something that is wrong with the work
  - Advisory, which gives advice on improving the work

The other three metrics of our automated metareview system—coverage, relevance, and plagiarism—relate both to the review and to the work being reviewed and will not be discussed in this paper.

The results in Sect. 41.2 have to do with comparing automated versus manual metareviewing. For the last several years in the second author's courses (on computer architecture, object-oriented design, and ethics in computing), students have received grades for their reviewing. These grades have been, depending on the size of the class, determined by the instructor, or by the instructor and teaching assistants. For the sake of time, students have not been given grades on individual reviews; rather, either the instructor or a TA has read all of the reviews they wrote on other students' work on a particular assignment and assigned an "average" score for those reviews. The average score has then been multiplied by the number of reviews done to assign a grade for reviewing. Some students have done a large number of reviews, in courses where extra credit has been given for extra reviews [4]. In the vast majority of cases, though, students have been consistent in their reviewing—either consistently careful or consistently careless—so per-student grades closely approximate per-review grades.

Section 41.3 covers a much larger set of reviews from a wide variety of disciplines. It tests the hypothesis that a long rubric will "fatigue" the reviewers into not providing much formative feedback to go along with their ratings. Section 41.4 places our work in context with other works that have been done on automated analysis of reviews.

41.2 Automated Versus Manual Evaluation of Reviews

We would want our automated metareviews to give better scores to reviews that would also be scored better by a human rater.

Hypothesis Metareview metrics for review quality produced higher scores for artifacts that are rated more highly by human raters.

Using reviews done by 112 students in four classes, we computed the correspondence between grades awarded by the instructor for reviewing and parameters derived by the automated metareview algorithm. Table 41.1 gives the Pearson's correlation.

All of the correlations are fairly low, and thus, it is difficult to say that any of the characteristics detected by the automated algorithm strongly influence the grade. Positive tone is positively associated with grade, which indicates that reviews that make positive comments on the work receive on average better scores than those that do not. Negative tone is also positively correlated with grades, which means that from the standpoint of review score, it benefits a reviewer almost as much to say something negative as to say something positive. However, neutral tone is almost uncorrelated with grade; thus, comments that do not judge the work do not help a reviewer earn a higher grade. This makes sense, because a review that hesitates to take a position on the quality of some aspect of the work is less likely to be useful to the author.

With regard to content, the results are counterintuitive. Summative content is probably the least useful to an author; just saying that some characteristic is good or bad will not help the author improve the work. Problem detection is almost uncorrelated with the grade, while advisory content is weakly correlated with improved grades.

Volume is correlated with grade, as we would expect. Typically, a longer review is one that says more about the reviewed work and thus is more likely to be useful to the author. But none of the correlations are very high. There could be several reasons for this.

Table 41.1 Correlation between automated metareview parameters and staff-assigned grades

Automated metareview parameter	Pearson's correlation with grades
Tone—positive	0.341
Tone—neutral	−0.0846
Tone—negative	0.266
Summative content	0.312
Problem detection	0.0110
Advisory content	0.186
Volume	0.308

First, the Pearson's correlation is high if there is a linear correlation between two variables. But reviews are graded on a fixed scale of 0–100, while reviews can have arbitrary amounts of positive tone, advisory content, etc. Up to a point, increasing the amount of useful content can earn the reviewer a higher grade. But students who meet the instructor's expectations are likely to earn high grades, and grades for students who substantially exceed the instructor's expectations will not be much higher.

Second, we usually desire to award students some credit for effort, even if their review is not very helpful. The first year that the staff graded the students' reviews, we awarded 45 % for a review that simply filled out the score dropdowns on the review form, but did not make any textual comments on the work. After a semester or two, it became clear that this was too generous, so we lowered that to 30 %. And after the second year, we warned students that we would not award any credit for reviews that did not make at least two suggestions for how to improve the work. But most of the reviews in the study were graded before we adopted this policy. Thus, the grades given to reviews were much more compressed than the range of any of the artifacts that our metrics were looking for.

41.3 Influence of Rubric Length on Review Length

It almost goes without saying that good rubrics elicit good feedback. A rubric must be detailed enough to draw the reviewer's attention to many salient aspects of the author's work. This suggests that rubrics should be detailed. However, it seems that if the rubric is very long, students feel less of an obligation to provide textual feedback, perhaps due to weariness or out of a sense that they are giving the author enough feedback by just checking boxes and filling out dropdowns. This suggests the following:

Hypothesis Review length (text submitted by students) will tend to vary inversely with rubric length (total length of all the rubric criteria).

To investigate this hypothesis, we chose all rubrics that were used in more than 50 Expertiza reviews. This set contained 76 rubrics. The rubrics contained several kinds of criteria.

- Likert-scale rating items, each with a text box for additional comments
- Checkbox items, where the reviewer would either check a box or not
- Text areas, where a reviewer could type a long comment, e.g., to summarize a submission or write a prose review.

Figure 41.1 is a scatter plot of review length versus rubric length, each measured in characters. Note that the points in this plot fall into a discrete number of columns. This is because each review that uses a specific rubric will have the same rubric length, although the length of review done using this rubric may vary markedly.

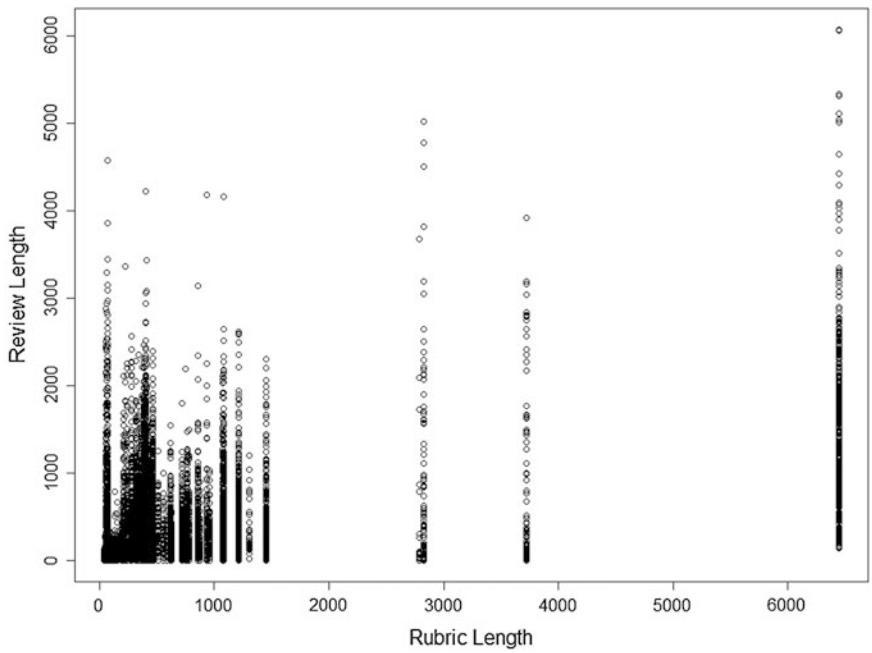

Fig. 41.1 Review length versus rubric length

From glancing at the plot, it is clear that longer rubrics are associated with longer reviews. The Pearson's correlation between review length and rubric length is 0.3225. Longer rubrics are not associated with shorter reviews. So the hypothesis is not confirmed. In fact, longer rubrics tend to induce longer responses from the students, though the effect is weak. Thus, from this sample, it seems that using a longer rubric is worthwhile.

However, if we exclude the 5 rubrics that have length >1500, a different picture emerges (Fig. 41.2). There is not an obvious correlation between review length and rubric length, and indeed, the Pearson's correlation is 0.1166. So rubric length and review length are essentially uncorrelated.

So, what's different about the longer rubrics? Well, four out of the five are used in courses in schools of education. It is not surprising that faculty involved in teaching education have a greater appreciation of the power of rubrics and that they are more motivated in encouraging their students to use them. Thus, rather than longer rubrics engendering more detailed reviews, it may just be that instructors who know how to use rubrics both write longer rubrics have their students write longer reviews.

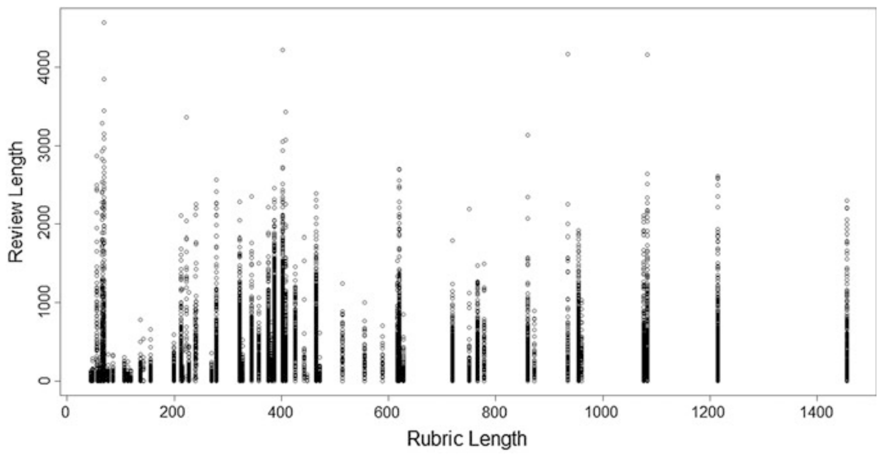

Fig. 41.2 Review length versus rubric length, for shorter rubrics

41.4 Related Work

This work, and the work cited earlier in this paper, is the first that we know of to apply multiple metrics to assessing the usefulness of peer reviews in an academic context. However, Xiong [5, 6] has used helpfulness metrics to summarize reviews in areas where the reader may be confronted with too many reviews (e.g., product reviews, hotel reviews). These build on earlier work on automatically assessing review helpfulness [7]. Similar techniques have been used for movie reviews [8]. Lu [9] attempts to rate the quality of reviewers using social network analysis.

41.5 Conclusion and Future Work

This work represents the first attempt at applying automated metareview rubrics to a large number of students' reviews. We expected that the automated metrics would give scores compatible with those assigned by human raters (in this case, the course staff). We found that the correlations between automated and manual scores were generally positive, but the degree of correlation was less than expected. It seems plausible that much of the lower-than-expected correlation comes from the fact that the metrics are linear, but we would hardly expect human-assigned grades to be uniformly distributed over the range of 0–100.

We also hypothesized that longer review rubrics might correlate with shorter reviews by students, because more of the feedback would be non-textual and because of the fatigue factor. However, we did not find such a relation. In fact, considering all review rubrics that have been used in more than 50 reviews in Expertiza, the correlation was positive, meaning that longer rubrics were associated with longer reviews. However, on closer examination, the longest rubrics and the longest reviews come from schools of education, which are likely to place the most emphasis on use of rubrics. This evidence suggests that students may benefit from using longer rubrics, because they draw their attention to a larger number of characteristics of the work being reviewed.

This study sets the groundwork for improving automated metareviewing. It suggests the use of nonlinear metrics for comparing automated and manual reviewing. Also, metrics that found to have little correlation with review quality can be removed from automated feedback to speed it up in cases where a reviewer is waiting for automated feedback before submitting a review.

In the immediate future, we are going to work on performance tuning of our other metrics—relevance, coverage, and plagiarism—which require processing both the submission and the review, so that analysis of the submission can be performed at the time it is uploaded. We can then apply these metrics to reviews done in systems such as Mobius SLIP [10] and CrowdGrader [11], which require *authors* to rate peer reviews and attempt to devise a composite metric that comes close to predicting how highly authors will rate a review. Once such a metric is devised, it can be presented to a reviewer who is about to submit a review, along with automated advice on how to improve the review before submission. This will serve our goal of providing authors with high-quality peer reviews.

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Chapter 42
What Peer-Review Systems Can Learn from Online Rating Sites

Edward F. Gehringer, Kai Ma and Van T. Duong

Abstract As their core functionality, peer-review systems present ratings of student work. But online ratings are not a new concept. Sites rating products or services have a long history on the Web, and now boast hundreds of millions of users. These sites have developed mechanisms and procedures to improve the accuracy and helpfulness of their reviews. Peer-review systems have much to learn from their experience. Online review sites permit users to flag reviews they consider inappropriate or inaccurate. Peer-review systems could do the same. Online review systems have automated metrics to decide whether reviews should be posted. It would be good for peer-review systems to post only reviews that pass an automatic quality check. Online rating sites give recognition to their best reviewers by means of levels or badges. Recognition is often dependent on upvotes by other users. Online review sites often let readers see helpfulness ratings or other information on reviewers. Peer-review systems could also allow authors to see ratings of the students who reviewed their work.

Keywords Peer-review systems · Online review sites · Reputation systems

42.1 Introduction

Online peer review is starting to come into its prime. Dozens of different Web-based applications have been used by hundreds of thousands, if not millions, of students. Systems have evolved a common set of functions, such as rubrics,

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reputation systems, and feedback from authors to reviewers. But, as frequently as peer-review systems are employed, their usage pales in comparison with online rating sites, such as TripAdvisor, Yelp, and Amazon.

The two kinds of systems share a common functionality. They are used to rate artifacts, whether the object is a research paper, an electronic device, a restaurant meal, or an auction seller. Online rating sites have nearly twenty years of experience in encouraging good feedback and vetting raters. Surely peer-review systems can benefit by studying what they have learned. This paper explores their features, and conjectures about how those features can be applied to peer-review systems. In Sect. 42.2, we look at mechanisms for assessing review quality. Section 42.3 examines how a peer-review system might incentivize good reviews. Section 42.4 discusses expressive techniques for presenting assessment data. We conclude with a summary of our findings.

42.2 Assessing Review Quality

42.2.1 Reputation Systems

To improve the accuracy of their ratings, online review sites need to know which reviewers are trustworthy. Simple reputation systems involve upvotes and downvotes. One *accumulative* metric is just to subtract downvotes from upvotes; the greater the margin, the better the reviewer. But this metric suffers from two shortcomings [1]. First, reputation scores have no fixed upper limit; thus, in an online auction system, they cannot indicate to the bidders which users are most trustworthy. Second, the reputation scores derived by the accumulative mechanism are vague. Suppose upvotes exceed downvotes by 100. This indicates a reasonably trustworthy seller if there are 103 upvotes and 3 downvotes, but a very risky actor if there are 11,100 upvotes and 11,000 downvotes. Further, once sellers accumulate sufficient upvotes (perhaps by selling relatively inexpensive items), a few downvotes have little influence on their reputation. So they are able to start auctioning expensive items and cheating buyers for quite a while before damage to their reputation becomes apparent.

To address this problem, the authors recommend using a time- and value-weighted metric. New votes count more than old votes, and votes are weighted by the value of the item. Time-weighted metrics could be used by peer-review systems to weight a reviewer's recent reviews more heavily than reviews from the beginning of the course, when the reviewer was less experienced. It is not so obvious how value-weighting could be used, but it might make sense to scale ratings by the point value of the assignment.

Suggestion 1: In determining a reviewer's reputation, the weight of old reviews should decay over time.

Another problem in online auctions is that a seller can create alias accounts and bid them in fake auctions to raise his/her reputation. The Lin et al. algorithm [1] circumvents this by weighting the value of upvotes and downvotes by the reputation of the user who casts them. This corresponds in a peer-review system to weighting the scores that a reviewer *r* assigns by the rating that reviewer *r*'s reviews receive from the authors reviewed by *r*. In this way, back-reviews are factored into reviewer reputations (which are in turn used as weighting factors in deriving peer grades). We know of no current review system that works like this, although systems such as CrowdGrader [2] and Mobius/SLIP [3] add in back-review scores as one component of peer-assigned grades. But these back-review scores *are not used to weight peer-assigned grades*. It seems that a system could make fuller use of back-review scores by using them as one factor in determining the reviewer's grade, as well as to calculate the grades of authors reviewed by that reviewer.

Suggestion 2: Incorporate back-evaluation scores of reviews ("back-reviews") into the decision of how heavily to weight the reviews of a particular reviewer in determining peer-assigned grades.

One potential downside of such a change is that it increases accuracy of grading at the expense of transparency: When the same inputs are being used in two different ways in the grading system, it will be harder for students to understand how their grades are being calculated.

StackOverflow's reputation system [4] encourages users to ask good questions and more importantly give useful answers to questions. The total reputation score of users is calculated based on the scores they earn from different categories. One feature is that StackOverflow weights upvoted answers and accepted answers much more than other answers. By doing this, the system encourages users to give as many useful answers as they can to earn their reputation. So, users with high reputation are normally users who have provided many helpful answers. The success of this approach is further support for factoring back-reviews into reputations. In addition, it suggests that authors be allowed to upvote or downvote not only complete reviews, but also textual responses to specific review criteria. For example, an author might upvote a reviewer's suggestion for improving the organization of the author's paper, as well as the reviewer's advice on the paper's bibliography. In a review system that gives reviewers more credit for having a good reputation, this could go a long way toward encouraging reviewers to make helpful comments on an author's work.

Suggestion 3: Allow authors to upvote or downvote specific textual feedback from reviewers, as well as whole reviews.

42.2.2 Manual Flagging of Reviews

It seems that most review sites, such as Amazon [5], TripAdvisor [6], and Yelp [7] have a mechanism for reporting fake reviews (Fig. 42.1). In principle, this is a good

Fig. 42.1 How to flag a suspect review on Superpages

idea. The core value of a review is its usefulness and honesty. Fraudulent reviews damage the objectivity of the system. In an online review site, there is an incentive for a vendor to fake glowing reviews of its own products or services, or disparaging reviews of its competitors. Flagging a review lets other readers know it is suspect (in a peer-review system, the only other readers would be the course staff).

Unfortunately, as reported on the pages linked to above, the flagging process does not work very well. The difficulty is that massive numbers of reviews are involved, and these are typically checked manually, although Yelp [6] has some automatic support. In a peer-review system used for a class, the numbers of reviews are usually much smaller. The Mechanical TA peer-review application [8] allows authors to flag reviews for scrutiny by the course staff, and it has not created a serious burden for the course staff. Expertiza [9] allows authors to bring review deficiencies to the attention of the reviewers themselves; this mechanism has greatly reduced the number of (off-line) complaints to the course staff.

Suggestion 4: In classes of “manageable” size, allow authors to flag unfair or disparaging reviews for examination by the course staff.

42.2.3 Automated Reviewer Vetting

The need to deal with fake reviews and rogue reviewers is not just limited to online rating sites; it is characteristic of any peer-to-peer system. Thus, P2P systems have developed mechanisms to deal with untrustworthy ratings. Azzedin and Ridha [10] outline a method for dealing with raters who change their “feedback behavior” to hide dishonesty or launch attacks on the rating system. This corresponds, in a peer-review system, to a reviewer who tries to rate others’ work harshly in an effort to look good by comparison; or to retaliate against a critical reviewer, e.g., by a harsh response (back-review) to the review. The article proposes an algorithm for outlier filtering. This algorithm assumes the majority of users on a review site are honest; their opinions about an artifact are considered mainstream opinions. Users who are dishonest will have opinions inconsistent with the mainstream; they are the outliers. The algorithm will filter out these outliers. The algorithm is applied only if there are contradictory reviews or comments. Other researchers have followed up with more sophisticated trust models. Meng et al. [11] employ a feedback-arbitration approach, which is robust even if unreliable reviewers collaborate. Thirunaryan et al. [12] apply Bayesian approaches. Some of these methods may be unnecessarily complicated for peer-review systems, which are unlikely to have to deal with conspiracies among reviewers, but their fully automated approach will be helpful for MOOCs, where any need for manual intervention creates a bottleneck.

Suggestion 5: Adopt a strategy for automatically filtering out "outlier" reviews when calculating peer-assigned grades.

An alternative to outlier filtering is simply to average the middle *k* percent of reviews. CrowdGrader [2] drops the highest quarter and lowest quarter of review scores, averaging the rest to derive a score for the author's work. It would be interesting to compare the performance of this strategy against the more refined approaches mentioned above.

42.3 Incentivizing Good Reviews

42.3.1 Ranking Reviewers

One way to reward reviewers for their work is to rank them in some way. Several online review sites use rankings to elicit more reviews, and reviews of desired types. For instance, Amazon ranks its reviewers based on other customers' opinions of their reviews. Each time a reader indicates whether a review was helpful, Amazon uses that vote, along with votes from other customers, to determine a helpfulness rating for that review (Fig. 42.2). A reviewer's rank is determined by the overall helpfulness of all their reviews, factoring in the number of reviews they have written. The more recently a review was posted, the more impact it has on the reviewer's rank [7]. The online review site Insider Pages ranks its members by two factors: the total number of reviews written and the number of times each member was the first to review a business [13]. This approach is designed to motivate reviewers to post feedback as soon as possible. Reviewer rankings create a motivation for reviewers to compete with each other in performing activities that the site wants them to perform.

The typical peer-review system assigns each reviewer a fixed set of reviews, so reviewers cannot compete in number of reviews. However, review systems such as Expertiza [9] and Coursera's peer-review platform allow reviewers to do extra reviews if they wish. Kulkarni [14] reports that 20 % of the students in Scott Klemmer's HCI MOOC did more peer reviews than required. Expertiza has obtained very high numbers of peer reviews (e.g., an average of 11 per student) by the simple expedient of awarding extra credit for extra reviews. Extra reviews are helpful—up to a point—but ultimately they overwhelm the author unless advanced

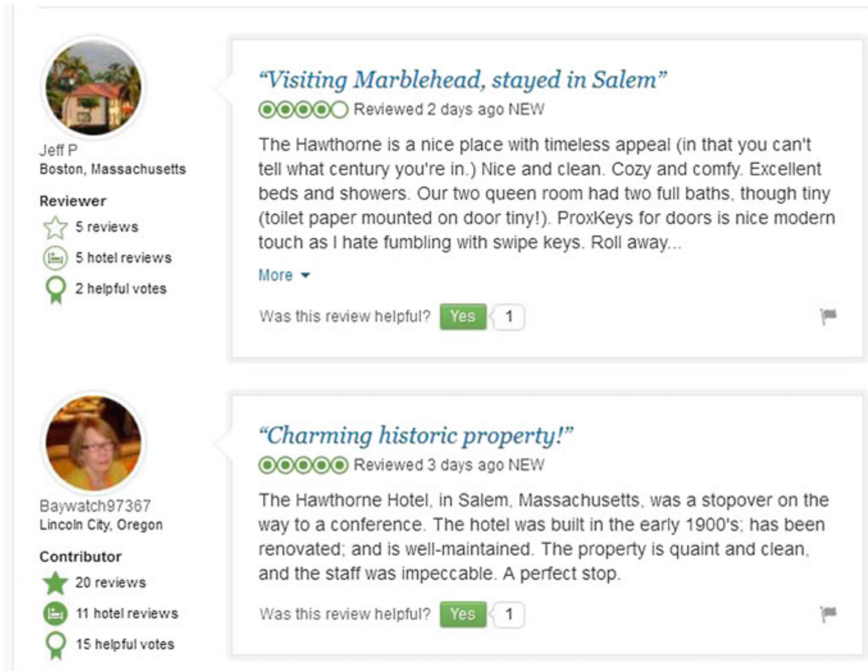

Fig. 42.2 TripAdvisor reviews, showing helpfulness tallies

techniques are used to display their content in a way that can easily be digested at a glance.

While it might not always make sense to encourage reviewers to compete in sheer numbers of reviews, there are plenty of other characteristics on which they might compete. Speediness of reviewing is one of them, since rapid feedback helps authors revise their work, while it is still fresh in their mind. Others include NLP-related metrics such as review relevance and review coverage [15].

Suggestion 6: Allow reviewers to achieve ranks based on characteristics such as number of reviews, promptness of reviews, or review relevance.

42.3.2 Reviewer Badges

Among online review sites, badges are widely used as an incentive to induce users to write high-quality reviews (Fig. 42.3). Badges differ from numerical ranks (or "levels"). They focus on specific characteristics of reviews, or specific connections with the community (as in Yelp). Yelp offers a set of badges which are oriented toward genres of restaurants (e.g., sushi). If a reviewer writes many reviews of sushi

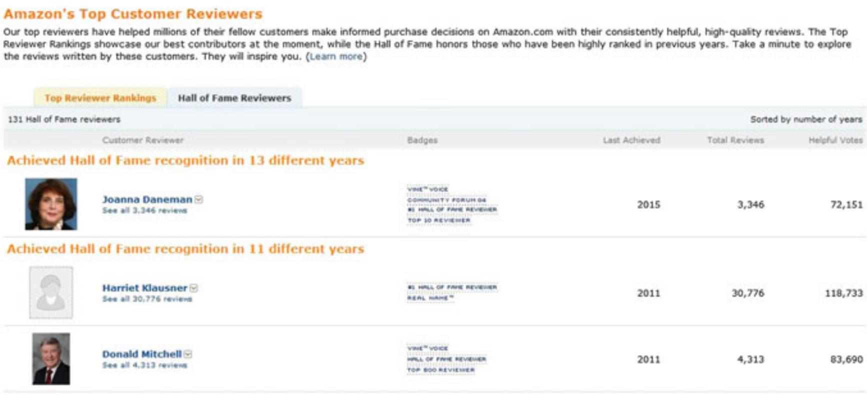

Fig. 42.3 Badges on Amazon, showing different users with different badges

restaurants, Yelp will detect that and award the user a "Sushi Sensei" badge. Yelp also provides an "Elite" badge [16], for a user who has expressed a strong connection with the local community. This goes along with Yelp's station as a location-based app that strongly relies on support from local users.

Considerable theoretical work has been done in optimal criteria for awarding badges [17, 18]. These deal with issues like whether badges should be awarded to a fixed number of users, or a fixed percentage, and whether the number of badge-holders should be made public. These evidently have yet to be applied to online rating sites, and applicability to peer-review systems would require further research to determine.

Suggestion 7: Allow instructors to create badges and to program criteria for awarding them into the peer-review system.

42.3.3 Leaderboards

Leaderboards are another way of incentivizing reviewers to commit more strongly to reviewing activities. For example, Amazon has a leaderboard named *Hall of Fame Reviewers* where they honor reviewers who have been highly ranked in one or more years. Reviewers who have been listed in this Hall of Fame also receive a *Hall of Fame Reviewer* badge and are recognized as long-term contributors to the community of Amazon users [7]. Zomato, an online review site about restaurants and food, has *Top Bloggers* and *Top Foodie*. These are two different leaderboards on their Web site. Top Bloggers [19] are based on total number of blogs a reviewer has posted on Zomato, while the Top Foodie is based on number of blog posts and photographs a reviewer has posted on the site. Leaderboards give reviewers an incentive to do their best on reviews in order to achieve community recognition.

They have on occasion [16] been used in peer-review systems. Users are allowed to hide themselves on the leaderboard if they desire.

Suggestion 8: Recognizing the most productive reviewers via a leaderboard may help motivate careful attention to reviewing.

42.4 Presenting Assessment Data

Peer-review systems are not known for offering students advice on how to get better reviews for their work. Indeed, general advice would be difficult to write, because it amounts to instruction on how to do good work, which is necessarily assignment specific. However, a few online review sites, such as TripAdvisor [5] and Zomato [19], do give tips to business owners on how to garner more favorable reviews. Most of the online rating sites have discussion boards where the subject is discussed ad nauseam.

A more practical way to understand why something was rated the way it was is to look at the characteristics of the reviewer. People tend to give positive feedback on things they are interested in. For example, customers who love sushi may rate a sushi restaurant more favorably than they would rate a barbeque place. Likewise, people tend to give negative reviews on subjects they subjectively or unconsciously dislike. Also, some reviewers have a more positive outlook than others, and they will tend to give higher ratings.

On TripAdvisor, for example, one can find out a lot about the reviewers of a property. Hovering over a reviewer's name will pop up a window showing where the reviewer lives, what "Travel Style" they have (e.g., foodie, history buff), show their badges, and give the distribution of reviews they have accumulated (how many "excellents," how many "very goods," etc.). One can click to see the reviewer's profile, with even more information, including where in the world they have been.

A peer-review system could also tell how many reviews a reviewer has submitted, and what their score distribution has been. If the same rubric is used for many assignments, it would be helpful to show how that reviewer has scored particular rubric criteria (e.g., if the reviewer is a stickler for organization). One might also want to see how many reviews, or comments in reviews, have been rated helpful by the authors. And it probably also makes sense to display the reviewer's reputation. Calibrated peer review [20] does not allow an author to see a reviewer's reputation directly, but the author can see how much weight each reviewer's score was given in calculating the author's grade. However, in a closed system like a class, saying too much about the reviewer's likes and dislikes, and what work they have reviewed, might compromise anonymity.

Suggestion 9: Provide authors with summary data on each of their reviewers' reviewing history.

It is also worth considering the converse: letting reviewers see how their authors have been rated by other reviewers. This helps reviewers gauge whether they might be being too easy, too superficial, or too hard on their authors. However, to avoid biasing reviews and promoting "groupthink," this information should not be shown until after the review has submitted the review in question. In multi-round assignments, where reviewers review the same submission more than once, any feedback should likewise be deferred until after the final-round review.

42.5 Conclusions

Peer-review systems face the same challenges that online rating sites do in showing readers that their reviews are believable. In this paper, we have identified nine features of online review sites that might be worth including in peer-review systems. We call them "suggestions" and not "recommendations," because each system should adopt only a cohesive set of features. Adopting too many features steepens the learning curve, complicates the review process, and increases the chance for students to misunderstand it. For example, if a system has a reliable way of filtering out outliers (Suggestion 5), it may not be necessary for it to provide a streamlined way for an author to appeal an unfair review (Suggestion 4).

While some of these features have been adopted by various review systems, we know of no studies addressing how much value is added by any of them. We look forward to work that compares the effectiveness of review processes that have one of these features versus a review process that lacks that feature. Twenty years into the online peer-review era, we should no longer limit ourselves to studies that simply measure whether or not peer review is a useful educational tool.

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Chapter 43
Peer Review Support in a Virtual Learning Environment

Martin Homola, Zuzana Kubincová, Jakub Čulík and Tomáš Trungel

Abstract In this demo paper, we provide an on overview of peer review facilities of our learning management system.

Keywords Virtual learning environment · Peer review · Tool

43.1 Introduction

In the educational context, peer reviews were shown to improve the engagement with the others' work; they provide a different type of feedback from a different point of view than the instructor's one [7]. Peer reviews foster discussion and experience exchange between the students, facilitating the social learning effect, a valued phenomenon according to the constructivist [3, 6] and constructionist [5] learning theories.

In this paper, we describe the peer-review functionality of the learning management system developed at our faculty that will be demoed during the PRASAE 2015 workshop. We first describe the generic workflow, then the functionality offered to the students, and finally that offered to the instructors.

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Lecture Notes in Educational Technology, DOI 10.1007/978-981-287-868-7_43

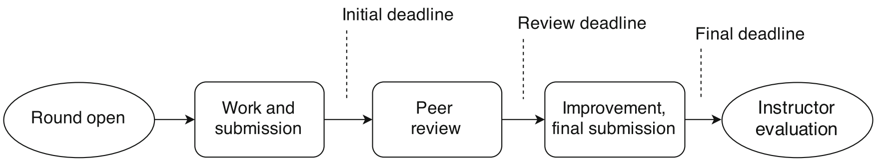

Fig. 43.1 Peer review process workflow diagram

43.2 Peer Review Workflow

Peer reviews are provided by the Assignments module. It allows the instructor to configure and publish assignments as well as to comment on submissions and reviews, and the students to submit their work and participate in peer reviews. Each assignment may be structured into multiple submission rounds. This allows for iterative submissions of the same work.

The workflow of a single round is depicted in Fig. 43.1. Once the round is open for submissions by the course instructor, the students work on the initial submission before the first deadline. Then, in the peer review phase, the students are assigned three submissions to review, which they do before the review deadline. In the next phase, they may improve their submissions before the final deadline. Once this deadline expires, the instructor evaluates the submission and the reviews as well.

The review phase and the improvement phase are optional and may be disabled by the instructor.

43.3 Student's View

The main student's view of the assignments is shown in Fig. 43.2 with an assignment ("Project") open. On top, the student sees information and the submission related to the current round. Below there is the listing of her own past submissions (in previous rounds). She may see the submission, and by clicking on "details" she gets to the submission page with reviews and feedback.

The submission page features all details of the given submission, together with the reviews for the submission (if there are any) and instructor's feedback once it arrives. The reviews are shown anonymously. The submission's author is able to rate the quality of the reviews.

Below the list of past submissions, the student sees also the list of reviews assigned to her in a similar form (not pictured). She is able to access each submission and its respective review form.

For each review, the students fill in a pre-structured review form consisting of a series of questions. The interface of a selected question is shown in Fig. 43.3. Each question features a hint/detailed instructions. The answer type is configurable; in this case, it is a numeric rating (1–5) combined with verbal justification.

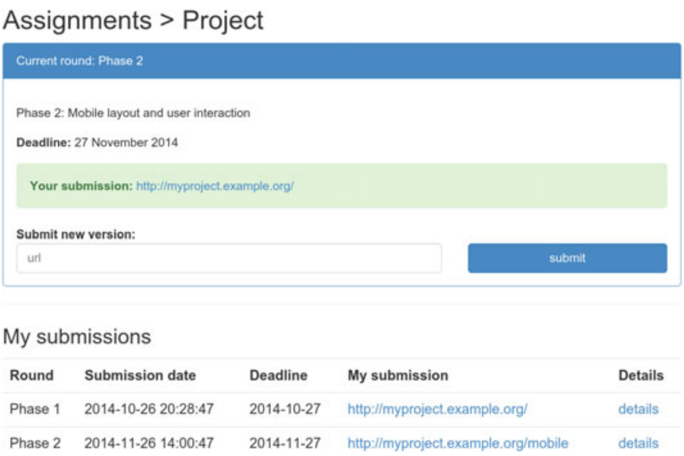

Fig. 43.2 Student's view of the Assignments dashboard

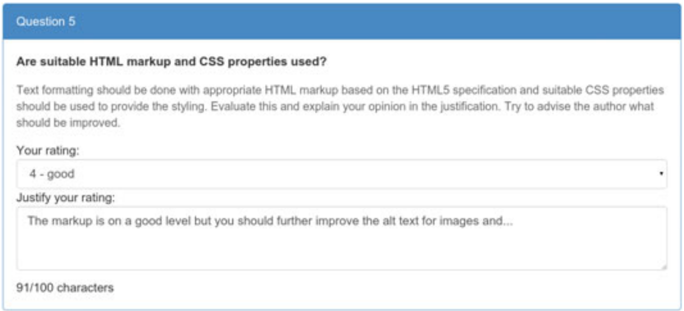

Fig. 43.3 Review form detail showing one of the questions

Once the review is submitted, the submission page of the reviewed submission is accessible to the reviewer. Other reviews are visible anonymously. This is useful for the reviewer to compare her assessment of the project with the remaining reviewers. The submission author's name is visible depending on the settings (blind vs. double-blind reviews).

43.4 Instructor's View

In the instructor's view, the assignment's main page contains the listing of submissions for all assignment rounds. For each submission, it lists the author's name, submission date, and the link to access the submission page. The submission page is as in the student's view but all students' names (authors and reviewers) are always showed, and there are forms for posting feedback on the submission and as well on the reviews.

The list of reviews assigned to each student in each round is also available in the instructor's view. For each review, there is a link to the respective submission page so that the instructor is able to compare it with the other reviews of the same submission.

In the configuration area, the instructor is able to add and remove assignments, configure the number of rounds, deadlines for each round, and the submission format (either URL or file upload). Furthermore, for every round, reviewing can be disabled and enabled, and the review type (blind or double-blind) can be set.

The review forms are fully configurable. They are structured into review questions, which can be freely added or removed. Every question has the question line and the hint, the latter is intended for more detailed instructions. There are three possible answer types: rating with the scale 1–5; verbal answer (free text); and the combined one—the rating scale 1–5 with verbal justification.

The review management also enables to assign submissions for reviewing: After the submission deadline is over, the instructor simply clicks the "Assign reviews" button and the system assigns each submission to three randomly selected students from the group of students who submitted in the given round.

Once the given round is finalized by the students, the instructor may evaluate both the submissions and the reviews. As mentioned above, she may post verbal feedback for both submissions and reviews, and in addition, she may grade these activities using a separate grading module of the system.

43.5 Conclusions

As described in Sect. 43.2, the whole multiple-round submission–peer review–resubmission–instructor-evaluation process is rather complex, as it involves setting and observing the deadlines, collecting the submissions, peer-review assignment, and configuration of structured review forms. With much smaller cohorts, this can perhaps be managed without a dedicated tool; however, with a slightly larger number of students, this would be infeasible. The tool is also very instrumental in assuring certain quality of the process, such as randomization of the review assignment, assuring that only the students who submitted their project are allowed to review, and enforcing minimum (or maximum) length limits on the review answer text.

Another important point is the methodology to be paired with such a tool. We covered this in our recent paper [2], as well in our older studies [1, 4], where the reader will also find a report of our results.

The described Assignments module is part of a larger learning management system that has been developed in collaboration with our students and it was used in our courses for last four semesters. In the future, we plan to extend the

Assignments module with further functionality, e.g., adding more discussion options on the submission page, and support for team assignments.

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Chapter 44
Grading Open-Ended Questions in an Educational Setting, via Non-exclusive Peer Evaluation

Maria De Marsico, Andrea Sterbini and Marco Temperini

Abstract A framework to allow (semi-)automated grading of answers to open-ended questions ("open answers") is presented. The grading is done by using both the peer (students) assessment and the teacher's evaluation of a subset of the answers. The Web of data, associated with peers' and teacher's assessments, is represented by a Bayesian network (BN). The students are modeled by their Knowledge and by the effectiveness of their evaluations (*J*). The answer grades in the network are represented as variables, with value in an estimated probability distribution. Grades are updated by evidence propagation and triggered by teacher's/peer's evaluation. The framework is implemented in the OpenAnswer Web system. We report on experiments and discuss the effectiveness of the approach.

Keywords Open answer questions · Peer assessment · Grade prediction

44.1 Introduction and Motivations

Grading answers to open-ended questions ("open answers") is widely considered as one of the best means to assess the educational outcomes of students performing specific learning activities. On the one hand, it allows evaluating the learner's skills and the achieved cognitive level [1], particularly in relation to the higher cognitive

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abilities [2, 3]. On the other hand, it requires a good deal of teacher's work. Making the grading task less cumbersome, yet preserving its reliability, would both be beneficial for the teacher and encourage wide use of open-ended questionnaires.

We have devised a framework to allow (semi-)automated grading of open answers. In our approach, we use peer evaluation, although not exclusively. Each student is requested to grade some (e.g., 3) of her/his peers' answers. However, the peer evaluation is strengthened by requiring that a "relevant" selection of answers is also graded by the teacher. Different strategies for "relevance" are detailed in the paper. We represent the Web of data, associated with peers and teacher's assessments, by a Bayesian network (BN), where the students are modeled by their Knowledge level on the topic (*K*), and by the effectiveness of their evaluations, denoted as Judgment (*J*: a variable depending on *K*).

In the network, the answers of a single student have an estimated Correctness (*C*: a variable depending on the Knowledge of the student). Such value is represented by a probability distribution and can be updated by evidence propagation. When a student marks an answer by a peer, a corresponding Grade (*G*) is added into the network, depending on both *J* of the student's and *C* of the peer answer.

The framework is implemented by the "OpenAnswer" Web-based system [4, 5]. It supports peer assessment, refined through the following iterative process, which starts after students have completed peer evaluation: (1) The teacher is requested to grade an answer, selected by a given "relevance" selection strategy; (2) the teacher's grade replaces the estimated *C*; this causes a propagated update on the Judgment (*J*) and on the Knowledge (*K*) variables of both the student that gave the graded answer and the peers that evaluated it, as well as of the Correctness (*C*) of all their (not yet graded) answers; evidence eventually propagates on the whole network. These steps are repeated until a given termination condition is met. The choice of possible termination conditions is detailed later. Once the termination condition is met, the teacher stops grading: Grades for the answers not yet graded by the teacher are derived by the present state of their *C*, and this completes the grading session. The system *Front-End* provides suitable interfaces to administer questionnaires and perform grading sessions (for both students and teachers). Its *Back-End* allows configuring and using the modules and managing the BN.

A first set of experiments gave encouraging results. This paper reports on the results from a second experimental phase. We analyzed strategies and termination options, to verify the effectiveness of the overall approach, in terms of correctness of system grading, amount of required teacher's work, and correlation of system outputs with teacher's grades and student's final exam grade. We report on a two-step process: (1) gathering data, by letting students answer questions and perform peer evaluation, and asking the teacher to grade all the answers, so to have a reliable ground truth; and (2) using such data to simulate several sessions of use of the system, where (parts of) the above teacher's grades are used, through the iterative process sketched above, to test different combinations of strategies and termination conditions and evaluate them.

44.2 Related Work, Intermixed with Motivations

Peer assessment [6] is an activity in which a student (or a group) is allowed to evaluate other students' assignments (and possibly self-evaluate own assignments). It can be organized in different ways, yet a basic aspect is that it can be considered as one of the activities in which social activities and collaboration among students can be triggered. It can also serve as a way to verify how the teacher can communicate to the students her/his quality requirements with respect to the learning topics: If this happens, assessments from peers and from teacher agree better [7]. Moreover, teachers may save grading time, or they could put it to better profit by analyzing how the students assess and self-assess: This provides more information about the students' ability to judge, and in turn about their knowledge. Therefore, peer assessment is growing as a crucial part in the educational process, allowing for a more active role of the student in the development of skills and in a perspective of collaboration (to some extent also with the teacher) and self-reflection [8]. In addition, large-scale peer assessment, like in Massive Open Online Courses (MOOCs), is known to achieve good marking accuracy results [9]. However, it is worth noticing that this may be due to the very large amount of information available. Moreover, notwithstanding the advantages, peer assessment may also suffer from biases, originated by several kinds of circumstances, such as friendship and reputation. Therefore, a mediated approach is sometimes preferred. This implies the direct handling of a subset of the assignments by the teacher, to preserve good accuracy and reliability of results even with traditional classes, where less information is available with respect to possibly huge online groups.

Our approach is a mediated one, and our main research question is whether it is possible to consider the system as a reliable substitute for the teacher in a relevant part of the grading work, allowing both to ease teacher's burden on each single questionnaire and to support a wider usage of assessment based on open-ended questions. This question translates, in our opinion, into the support of the OpenAnswer framework to a twofold kind of modeling (one explicit and another implicit): 1) student modeling—it is managed as explicit representation of skills, also relevant for the system to compute the final grade of peer-assessed answers; and (2) teacher modeling—this is not explicitly given in the BN, and yet can be witnessed by the influence that teacher's grades and assessment criteria have on the overall behavior of the framework. We are also interested in a second research question: the possibility to use the student model maintained in the system, for an evolving prediction of her/his performance, in a course where open-ended questionnaires are used on a regular basis and on its various topics. The measures adopted to ponder about the possible answers to our research questions are discussed in Sect. 44.5.

In regard to the automatic analysis of open answers, several approaches have been proposed, not only for education. These also differ with respect to the different degrees of human intervention they require. Applications from data mining tackle the problem of summing-up opinions out of marketing-oriented questionnaires [10].

In [11], concept mapping is applied to evaluate "coding schemes" to label semi-automatically answered parts, for classification of answers. (Semi-)automatic approaches, in education, have been proposed [12] through the use of ontologies and semantic Web technologies (to label ontological components of answers against the exact one). A use of open answers to determine the implicit students' (mis-)conceptions and the related treatment is in [13], where this activity acts as a cognitive diagnosing tool in an intelligent tutoring system on algebra.

44.3 The Assessment Framework

As mentioned, the framework supports the use of peer evaluation, exploited in the first phase (*marking*, by students) and mediated by a second phase (*grading*, by teacher).

In the marking phase, the students are requested to answer a question. In our present experimentations, we use one question at a time related to the course topics, in order to better highlight peer assessment dynamics. Each student also provides an assessment over the answers by a subset of the peers (usually 3). Questions, defined by the teacher, are annotated by assessment criteria.

For each student, the system maintains an individual model built as a BN. The variables of the BN represent the learner's state of Knowledge on the question topic (K) and her/his ability of Judgement (J) of peers' answers on the same topic. During the marking phase, the individual students' networks are connected through the Correctness (C) of an answer (inferred by the system, or possibly, later on, stated by the teacher) and the Grades (G) the student gave to peers' answers.

In this setting, C and G control the evidence propagation in the BN, in the first phase, basing only on peer assessment (G) and then, in the second one, also according to the grades (possibly) provided by the teacher (C). During grading phase, the system supports the teacher in the job: (1) by suggesting an answer to grade that, according to one of the selection criteria detailed below, will add more significant information in the overall BN; (2) by propagating in the network the added information provided by the teacher's grade: When the answer is marked by the teacher, the initial C distribution of probability (conditioned by K) becomes a fixed value, with propagation effects on the J variables of the peers that assessed that answer, indirectly on their K, directly on the K of the student giving that answer, and eventually on the whole BN; (3) by iterating the previous steps until a termination condition is met, stating that new information coming from additional teacher's grades would be less decisive; and (4) by releasing the answer final grades: those directly given by the teacher and those inferred basing on the present probability distribution of the associated C for the others.

The BN variables are modeled according to the following observations:

- J is at a high cognitive level in Bloom's taxonomy; this implies a dependency from K: $P(J|K)$ is the corresponding conditional probability table (CPT);

– C is supposed to be dependent on K as well, by the $P(C|K)$ CPT;
– For C and G, we adopt the well-known grading range [A,…,F], mapped over decimal rating as follows: F comprises marks in [0, 5.5), E is [5.5, 6.5), D is [6.5, 7.5), C is [7.5, 8.5), B is [8.5, 9.5), and A is [9.5, 10].

In an OpenAnswer session, a set of variables is instantiated for each student (K, J, C, and a G variable for each peer assessment given by the student). K and J are in the interval [A, F] as well. Once the network is created with the initial evidence, the initial probabilities are computed by the Lauritzen [14] belief propagation algorithm.

We have devised two basic selection strategies, plus a random-based one, for suggesting the "next best answer to grade" during the grading phase, as sketched above:

– max_wrong: selects the answer most probably mapping onto F: The rationale is that a student would more easily accept F if coming directly by the teacher;
– max_entropy (ME): selects the answer showing highest entropy on C; the system knows less about it, since the associated G variables (peer grading) hold very different values, and its grading would pour more information in the system;
– Random: selects randomly the next answer; this strategy is mostly used for testing purposes, to mark the difference with a motivated strategy.

Two families of termination criteria for the teacher's grading are applicable:

- if max_wrong is the strategy to select the next answer to grade, we may apply:
  – no_wrong: The process stops when no answer would be automatically graded F by the system (F probability = 0)
  – no_wrong2: as above, but with F probability $\leq 1/2$;
  – no_wrong3: as above, but with F probability $\leq 1/3$
- if max_entropy is the strategy to select the next answer to grade, we may apply:
  – no_flip(N): The inferred grades corresponding to C variables have not changed in the last N correction steps (we use N = 1, 2, 3)
- If random is the strategy, any of the above termination criteria can be applied.

44.4 The OpenAnswer System

OpenAnswer is a Web-based educational environment, whose users are teachers and students. The system is implemented in PHP, with data stored and managed through XML and a MySQL database. It includes a *Front-End* and a *Back-End*.

The Front-End provides functionalities which depend on the class of user. It allows teachers to define questions and questionnaires, to administer questionnaires, and to proceed to assessing the answers, possibly (yet not necessarily) with the support of the system. The same Front-End allows students to work on questionnaires (by answering and peer-assessing answers) and see the results of such work, in terms of grades obtained in the questionnaires and present state of their model (*K* and *J*).

The Back-End of the system allows managing the computational and representational aspects related to the representation as connected BNs of students, teachers, and answers. It further implements the available selection strategies and termination conditions explained above, to support the teacher's evaluation work.

A teacher is associated with each "subject matter area." She/he can define questions and assessment criteria related to such area. An editor allows defining them as formatted text enriched with images and other multimedia resources. It is possible to configure a new questionnaire by selecting among the available questions, and contextually associating with each of them one or more of the defined assessment criteria (Fig. 44.1).

A questionnaire can be used in different contexts and with different options of peer assessment, i.e., it can be administered in one or more "sessions." A session configuration describes the use of a questionnaire by specifying (i) how many questions make up the questionnaire, (ii) how many answers will be evaluated by each peer, (iii) whether the peer will know the name of who submitted the answers (s)he assesses, and (iv) whether self-evaluation (peer assessing one's own answer) is possible (Fig. 44.2).

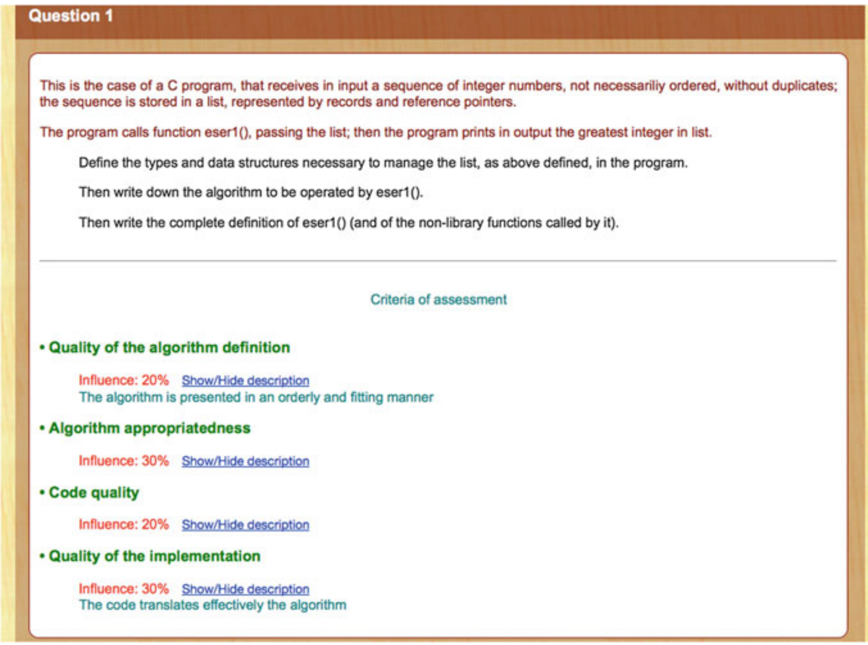

Fig. 44.1 OpenAnswer Front-End: a question associated with its assessment criteria

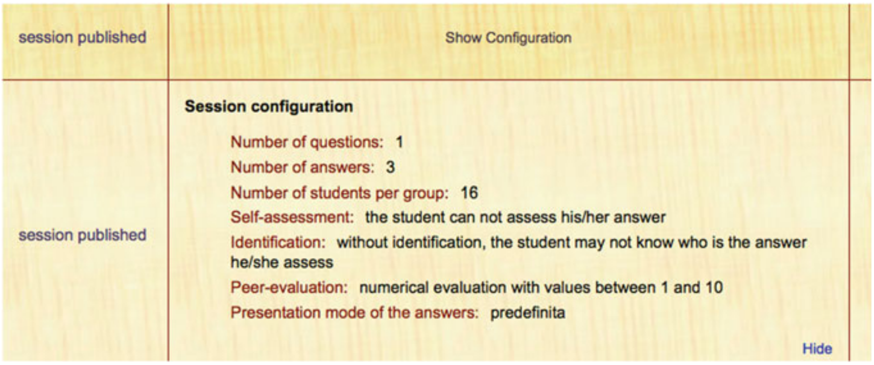

Fig. 44.2 Session configuration (How the questionnaire will be administered)

During students' activity, the system stores their answers and their peer assessments. At the end of this activity, the assessment phase performed by the teacher can start. It develops as an iteration of the steps detailed above: (1) The system suggests the next answer to grade (it appears on top of the list of answers available to the teacher); (2) the teacher selects an answer to grade (the teacher is free to choose a different one than the first in the list, although the system would follow a more stable process if the teacher accepts the suggestions); and (3) the teacher assesses the selected answer.

44.5 Evaluation and Tuning of the System Components

As mentioned in Sect. 44.1, the main aim of this experimentation was to evaluate the relative reliability of the different selection strategies and termination conditions we had devised. At the same time, we also wanted to validate our framework of mediated peer assessment, according to the research questions stated in Sect. 44.2. We are reporting on tests performed according to a two-step method:

1. Data-gathering step—by using the OpenAnswer system, the students answer to questions and peer evaluates them; in this step, we ask the teacher to grade all the answers, in order to have a reliable ground truth for final marks.
2. Simulation step—by using the gathered data through the framework's logic, we simulate several sessions of use of the framework; (a possible subset of) the teacher's grades stored in the previous step are exploited in the same order and amount as it would be requested/submitted in a real situation, according to different combinations of strategies and termination conditions per session.

As of the first research question, we measure the following in each simulation:

- Length (*L*) of the teacher's grading session, i.e., the number of answers graded directly by the teacher representing the actual teacher's grading job;
- System accuracy: It is represented by the number of answers whose grade, when compared with the ground truth, was found to have been inferred exactly by the system (OK) or is within a distance ≤1 votes (IN1) from the exact one; in other words, for the answers considered to measure this outcome, the exact grade is the one given by the teacher during gathering of ground truth data, but it is not used in the simulation that rather uses and propagates the value inferred by the system;
- Correlation of the grade inferred by the system with the exact one, for each answer.

The second research question is tackled by analyzing the correlation (Pearson) of the student model (*K* variable) with the grade in the final exam of the whole course.

The sessions we simulated allowed computing the abovementioned values with respect to the various combinations of strategies and termination criteria. The sessions were simulated using the ground truth data provided by the data-gathering step. The collection entailed three separate and sequential stages, involving three questions on computer programming, at undergraduate university level (first year): In the first stage, two groups of 13 students participated; in the second stage, two groups of 11 students participated; and in the third stage, two groups of 9 and 11 students participated. Except for the missing ones, the students were always the same.

Coming to the first research questions, Table 44.1 shows some data deemed to help performance evaluation: *L* is the Length of the grading phase, expressed as the percentage of answers for which the direct teacher's grade was used in the simulation. Accordingly, OK is the percentage of grades inferred exactly by the system alone (computed from *C* as equal to teacher's grade); so (OK + *L*) is the overall exact grading produced by the system. Then, IN1 is the percentage of grades inferred by the system having a difference of not more than 1 vote from the exact grade (in ground truth), and IN2 is the percentage of grades inferred with a difference of not more than 2 votes from the exact grade (it does not imply a particular claimed quality; rather, it is used just to give a sense of closure to the picture). INFERRED is the total number of grades inferred by the system, so the ratio OK/INFERRED (and in some measure also the ratio IN1/INFERRED) might be considered as a representation of the overall performance of the grade inference. In this table, we compare various combinations of strategies to select the next answer for the teacher to grade (including random selection) and related termination conditions. We also consider an additional strategy using only peer evaluation ("none," i.e., no teacher grading). Darker cells represent good results (such as *L* not greater than 50 %, OK + *L* at least 60 %, IN1 + *L* at least 80 %, and OK/INFERRED greater than 30 %). *Lighter gray cells* point out good results yet associated with bad values for *L* (e.g., OK/INFERRED = 36 % is good, but it comes from a vexing 67 % of teacher's grades).

Table 44.1 Performance comparisons on strategies and termination conditions: *ME* max_entropy strategy (applying only no_flip termination conditions); *MW* max_wrong (using only nowrong* term. conditions); "none" means "no teacher grading" and corresponds to pure peer assessment in OpenAnswer; RANDOM means random selection of next answer to grade (using all our term. conditions)

	noFlip(1) (%)	noFlip(2) (%)	noFlip(3) (%)	none	nowrong (%)	nowrong2 (%)	nowrong3 (%)	
L	24	41	54	(0 %)	26	12	26	ME – MW
	26	50	67	–	65	41	46	RANDOM
OK + L	46	60	67	30 %	44	36	44	ME – MW
	50	63	79	–	75	56	62	RANDOM
IN1 + L	78	82	86	67 %	79	71	79	ME – MW
	76	83	85	–	91	81	85	RANDOM
IN2 + L	96	96	97	95 %	98	96	98	ME – MW
	94	96	99	–	100	97	100	RANDOM
OK/INFERRED	31	36	36	30 %	26	29	26	ME – MW
	34	25	19	–	41	32	36	RANDOM
IN1/INFERRED	72	72	76	67 %	70	67	70	ME – MW
	69	65	30	–	74	75	77	RANDOM
IN2/INFERRED	95	94	95	95 %	97	96	97	ME – MW
	92	92	86	–	100	93	100	RANDOM

Sadly, it does not seem so far that our selection strategies particularly improve over the random one. A random choice does a good job (yet notice that it necessarily exploits our termination conditions). On the other hand, ME selection of next answer for teacher to grade, with no_flip(2) termination (C did not change in last 2 answer grading), gets the best result: OK/INFERRED = 36 % and L = 41 %.

This would allow to conclude also that the influence of the termination conditions is greater than that of the selection strategies, which is somewhat expectable.

The comparison with "none" ("pure" peer assessment) is represented by making the cell with label (OK + L) represent the percentage of grades correctly inferred from the overall peer assessment and only from it (when compared with ground truth provided by the teacher); the cell with label (IN1 + L) represents the percentage of those inferred at a distance ≤1 vote, and similarly for the others.

To reach a conclusion regarding the first research question, we also checked the Pearson correlation between the grade inferred by the system for an answer and the exact (teacher's) one. Table 44.2 shows such correlation: The best, and more stable, correlation is still for the ME strategy; the "pure" peer assessment conducted in the framework (none) has also a good correlation. The grading inferred by the OpenAnswer system seems to be quite well correlated with the teacher's grading, confirming an effective influence of the teacher in the system. The table also reports on the correlation between the "raw" marks provided by the peers (not operated by the framework) and the teacher's grade. This correlation is really low (0.25); this lets us conclude that the "quality" of the unprocessed assessment was low as well, and it could not be realistically used for grade prediction. On the other hand, the OpenAnswer framework, basing on the same data only (in the case "none"), reaches

Table 44.2 Correlation between inferred grade and teacher's grade, on all answers

none	0.76
ME + no_fliips	0.81 – 0.84
MW + nowrongs	0.59 – 0.69
RANDOM + noflips	0.62 – 0.73
RANDOM + nowrong:	0.47 – 0.56
MARK – GRADE	0.25

a much higher correlation with the exact grade (0.76): this should allow to conclude that the approach, per se, is reasonable. Then, when allowed to exploit the teacher's grades, the correlation increases to quite good values (ME) between 0.81 and 0.84.

The data discussed here cannot allow to say that OpenAnswer is ready to be deployed in real-life classrooms: The amount of work still required to the teacher in the better cases, and the overall success rate of the inferred grading (OK) is still not good enough in our opinion. As for the latter, we would aim at achieving an OK/INFERRED of 75 % at least, with a consequent IN1/INFERRED of 90 % at least.

On the other hand, the data analysis, the comparison with "none" and "RANDOM", and ultimately the observation that a kind of influence of the teacher in the system does exist, allows to draw a confirming answer to the first research question of Sect. 44.2.

As of the second research question, Table 44.3 reports on the correlation between the value *K* for the single student, after the end of the session simulation, and the grade obtained by the student in the final exam. The best results are in dark (gray), and generally, ME performs better. We remind that the simulations are regarded as a three-stage process, involving the same students and three successive questions, and we have to point out that the student's *K* holding at the end of a given grading simulation for a question was used as starting state in the successive (simulated) grading session for the next question. In this table, the data are regarded as the last stage, so it can be considered as representative of the "presently final" student model. As such, even after only three peer assessment sessions, the model shows a good correlation with the final grade in the course. The (three) questions used are related to just a part of the topics treated in the course, and so are not totally covering the exam topics; on the other hand, the final exam usually involves a selection of course topics. We can conclude that the evolving model managed by OpenAnswer is promising as a prediction means for student performance, able to suggest, if needed, the timely administration of remedial activities.

Table 44.3 Correlation between *K* and the course final exam grade of the students

noFlip(1)	noFlip(2)	noFlip(3)	none	nowrong	nowrong2	nowrong3	
0.71	0.69	0.72	0.53	0.60	0.54	0.60	ME – MW
0.66	0.57	0.63	–	0.46	0.59	0.74	RANDOM

44.6 Conclusions

We have shown promising quality results for the OpenAnswer assessment framework. There is space for improvement on both the BN model and the selection strategies for the next answer to grade. Regarding the BN model, the CPTs we used could be improved at least by parametrizing them and then optimizing with respect to the inference output quality. Moreover, learning them from examples, through machine learning techniques [15], might improve the model. This is not yet possible, given the limited size of our actual datasets. Regarding the strategies, the ME selection strategy shows comparatively good performances. A selection strategy that does a deeper analysis of the information gain obtained by its grading could be even more effective.

Moreover, we have noticed some inconsistencies in some student peer assessment, (like if they were not really interested in doing a good job). By finding these students and managing them differently, we think we could improve the model.

Finally, we have seen evidences of an influence of the teacher in the assessment framework that can prelude to a more explicit definition of a teacher model related to peer assessment. This could be done by defining for the teacher an instance of the same subnetwork template used for student, connected through a G variable for each graded student. This would allow modeling the participation of more than one teacher/grader.

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Chapter 45
A Wiki-Based Approach to Computer-Assisted Translation for Collaborative Language Learning

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Abstract The role of translation in second language learning has long been recognized. With the advent of social collaborative platforms, its importance can be further emphasized. In this paper, we propose a social collaborative platform based on the popular MediaWiki, together with its Translation extension, that aims to align translation technology and second language learning to create a collaborative environment, thus enabling high-quality learning experiences. The platform has been developed in the WALLeT (Wiki Assisted Language Learning and Translation) project in Tor Vergata University of Rome, and it is currently being tested in two university courses, English and Spanish, for students enroled in the *Languages in the Information Society* Degree.

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45.1 Introduction

In this paper, we describe a novel approach to language learning that merges three distinct but related areas: computer-assisted language learning (CALL), computer-assisted translation (CAT), and collaborative learning (CL). Whilst there have been several studies, from both a theoretical and a practical point of view, involving two out of the three mentioned areas, to the best of our knowledge this is the first attempt to connect all these three areas to provide beneficial effects for language (and CAT) learners. Indeed, previous approaches showed the mutual benefits of CL and CALL [28], CALL and CAT [12], and CL and CAT [5].

Our approach is based on a platform that we developed in the Wiki Assisted Language Learning and Translation (WALLeT) project at the Tor Vergata University of Rome. This platform is based on the popular MediaWiki and its Translation extension translatewiki, which allows embedded CAT functionalities and, in particular, to access the Translate Toolkit tmserver, a Web server for translation memories.

The aim of the WALLeT project is to align translation technology and second language learning to create collaborative environments that enable high-quality learning experiences. Pivotal principles, such as autonomous and networked learning, connectivity and interactivity in Wiki domains, open-source education, flexible scalability, and cost-effectiveness, are at the basis of WALLeT. The project is divided into two main steps: the first one is the implementation of a Web-based platform for collaborative CAT, based on open-source technologies, whilst the second one is a field test of this platform in two university courses, English and Spanish, for students enroled in the *Languages in the Information Society* BA Degree and in other degrees at the Tor Vergata University of Rome.

Several studies (see, e.g. [12]) show that language learning can be positively supported by a functional use of translation since many scholars consider it as the fifth skill. The combination of translation competences along with translation technology skills acquisition allows to reduce interference and make students aware of the fact that there does not exist a one-to-one correspondence between two languages. Working on collaborative translation tools, in order to implement and optimize them, helps student develop their cognitive problem-solving and decision-making abilities. At the same time, it enhances their awareness of lexical specificities and syntactic patterns in specialized domains. On the other hand, the investigation concerning the language area will focus basically on the lexical–terminological issues combined with the lexical–syntax interface. Diverse specialized fields, such as economics (business and financing), the medicine (human and animal health), life sciences (nutrition and biology), social sciences, engineering, and IT, will be the domains of the lexical and terminological analysis. Students will be required to collaborate in the construction of specialized corpora (both monolingual and parallel), terminology databases, translation memories, and project and learning management tools to be utilized and embedded in the new platform. This gives students' access to linguistic and discursive features typical of professional communities.

In this paper, we provide an overview of the WALLeT project and describe its implementation and test plan. The paper is organized as follows: In the next section, we discuss CAT and CALL, whilst in Sect. 45.3, we address translation memories. Open-source Wiki software and extensions are briefly described in Sect. 45.4, and Sect. 45.5 presents our WALLeT platform. We finally detail our learning project in Sect. 45.6.

45.2 CALL and CAT

There is a vast offer of free Web-based language learning tools for a variety of languages, often associated with promises of a fast development of language abilities. However, the choice is often limited to the acquisition of very basic skills with a low supervision quality, since it often relies on tuition provided by native speakers rather than teachers. Examples of such widespread platforms are Duolingo,[1] Busuu,[2] and Lang-8.[3] A student who wants to achieve significant skills within the European reference framework is often addressed to paid assistance.

On the other hand, both companies and academic institutions offer serious online language learning platforms. The most notable example of a commercial platform is the Rosetta Stone,[4] which, though it claims to be adopted by over 20,000 educational institutions, is a proprietary one, with no control by the institution using it. Many academic institutions offer online tuition within the framework of an educational path leading to a BA or MA degree in foreign languages. A well-known example of such a platform is the Open University,[5] whose remote study orientation dates from its foundation. Another significant example for its variety of online resources is the Language Centre[6] at the University of Cambridge.

Though we cannot provide an exhaustive survey of the worldwide offer of online academic platforms for language learning, we remark that their focus is not on translation and on the acquisition of the metalinguistic competence, language learning being pursued by means of traditional activities (listening to audios and watching videos, reading excerpts from books and magazines, doing grammar exercises, interacting with an online tutor, etc.).

At the same time, the panorama of CAT tools is represented almost entirely by costly software (with the notable exception of the free tool OmegaT[7]), addressed to

[1] www.duolingo.com.

[2] www.busuu.com/.

[3] http://lang-8.com.

[4] www.rosettastone.it.

[5] www.openuniversity.edu/Languages.

[6] www.langcen.cam.ac.uk/lc/.

[7] www.omegat.org.

professional translators. The most relevant example of a Web-based translation platform is translatewiki.net, which is powered by the Translate extension for MediaWiki.

Summing up, though tools exist for online language learning and translation, they appear to be developed without crossing each other's path, with no attempt to employ translation as a learning tool for a second language. Again, though we cannot provide an exhaustive survey, there is no evidence of projects carried out by universities aimed at implementing open access and collaborative resources for technical translation applied to second language learning.

45.3 Translation Memories

Translation memories are the essential bricks of any CAT tool. They contain single words and segments together with their translation (i.e. bilingual corpora of previously translated phrases), allowing for their quick use in a translation task. A CAT software must therefore incorporate the right tools both to build the associated database using the current translation task as an input and to use previously built translation memories. The advantage brought by translation memories as to translation speed is undeniable. Even when building a translation memory from scratch, it has been estimated that at the third translation task, the time saving in the translation process is already 20 % [4]. Translation memories are nowadays routinely incorporated both in commercial products and in open-source ones.

Though they have typically been considered as a companion to an individual software product, the problem of their sharing across a community of translators has led to the development of a distributed translation memory through the use of Web services [11, 31]. Relying on a distributed approach allows to leverage the efforts of the whole community, building a larger database in a shorter time with a lower individual effort. Our approach to build a Web-based platform for CAT is therefore a natural candidate to experiment with a shared translation memory.

Translation memory services have been enabled on Wikimedia projects since August 2012,[8] but a translation memory service had been in use at translatewiki.net for years. After more than a year of development, which encompassed some changes of approach, the service is now available for all of us. Full-text search, essential to any translation memory, is accomplished through the Solr open-source platform, which is written in Java. The developers themselves regret the use of the Levenshtein algorithm to match the text to the translated terms and segments in the memory, since it is considered as rudimentary for such a purpose [22].

[8] http://laxstrom.name/blag/2012/09/07/translation-memory-all-wikimedia-wikis/.

45.4 Wikis

A Wiki is a platform that allows users with only a Web browser, to easily create and edit pages, in a collaborative manner. The original idea of a Wiki platform is owed to Ward Cunningham [20], who implemented the first prototype, which almost immediately inspired several variants [23].

A Wiki can be briefly described as a (simple) Web page in which there is an edit button that allows to enter an editing mode to modify the content of the page, using a simple non-WYSIWYG (What You See Is What You Get) markup language. This process might sound difficult for the non-technical user, but indeed, the Wikis proved to be more than usable [9], with few problems related to the hyperlink management.

As observed by Popescu in [25], in an educational setting, Wikis can be used to provide support for several learning activities including: "*produce a collaboratively edited material (collaborative writing task); incrementally accumulate and organize knowledge; document each stage of a project; provide feedback on peers' writing; publish a summary of readings or a critical review of the literature; comment on teacher published material and ask questions; annotate lecture notes published on the wiki and share annotations; integrate resources from different Web sources; contribute to a public wiki (e.g. Wikipedia) and consequently receive feedback from a wider community*". Recently, several works in the literature have discussed the benefits of using Wikis in an educational setting. Amongst these works, the most relevant to our purposes are the two surveys by Parker and Chao [24] and Kummer [19], two papers that describe some negative experiences [6, 10], and two papers that, on the opposite, report a general positive effect of Wikis in learning [14, 25].

45.4.1 Adapting Wikis to Education

Despite their popularity in education, Wikis are platforms that have not been specifically designed to support learning, and thus, they lack some basic functionalities such as students' management, evaluation support, and learner monitoring. Several Wiki extensions have then been proposed to support learning activities including:

- **CoWriting Wiki** [1], which extends the open-source ScrewTurn Wiki.[9]
- **EdDoku Wiki** [26], which extends the open-source DokuWiki.[10]
- **Tracking Bundle** [18], which extends the open-source MediaWiki.[11]

[9] http://stw.codeplex.com.

[10] http://www.dokuwiki.org.

[11] http://www.mediawiki.org.

- **ClassRoom Wiki** [16], which is a dedicated Wiki platform.
- **CoLearn** [27], which also extends the open-source MediaWiki.

A comparison between the first four platforms in the list above has been presented in [17]: we refer the interested reader to works [17, 27] for a comprehensive overview of this topic.

45.4.2 CAT Tools for Wikis

The problem of content translation in Wikis has been addressed in [8], where the authors discussed traditional translation against the needs of Wiki users, thus showing some peculiarities of translation on a Wiki platform. In particular, they argue that the advent of Wiki platform supports an incremental just-in-time translation process rather than the traditional sequential translation (translation starts after the original text is frozen) or parallel authoring (authors write the text in parallel in different languages, after being briefed on the contents, and align with one another during the writing process).

However, Wiki platforms do not natively support translation activities. Despite their large popularity, the only example of (mature) CAT tools for Wikis is the Translate[12] extension for MediaWiki, which powers the translatewiki[13] Web-based translation platform, supporting the translation of content for open-source projects, such as MediaWiki itself and OpenStreetMaps. Furthermore, the Translate extension supports also translation memories and machine translation with external tools (tmserver, Apertium, Microsoft, Translator, Yandex.Translate).

The implementation of massive online collaboration is however expected to have a huge impact on translation practices. Désilets noted that we can expect to have a more chaotic translation workflow, where original documents are produced in a variety of languages, and translation is not mandated but rather the result of a voluntary process, so that multilingual contents shall not be developed starting from English and may take longer than in the past. On the other hand, massive collaboration can allow translators to share glossaries and exchange suggestions on an unprecedented scale [7].

45.5 The WALLeT Platform

The core of the WALLeT platform was implemented using MediaWiki, together with its Translate extension. MediaWiki is a very popular and robust platform written in PHP, originally designed for use on Wikipedia. It has a strong and active

[12] http://www.mediawiki.org/wiki/Extension:Translate.

[13] http://translatewiki.net/.

Fig. 1 The steps to mark a text for translation: insertion of the <translate> markup (*left*) and the choice of the target languages (*right*)

community of developers, and there are several extensions available, developed either by the community itself or by independent coders.

Amongst the dozens of extensions available, the Translate extension is as we mentioned in the previous section, very popular and stable: indeed, the translation of Wikipedia pages is accomplished using this extension and the Wikipedia page about this extension states that it "*makes Media Wiki a powerful tool to translate all kinds of text*".

In order to translate a(n existing) page, the user has to perform the following steps, shown in Fig. 45.1.

1. Marking the page, or a subset of it, for the translation, by editing it and adding the <translate> markup around the text to be translated.
2. Choosing, amongst the languages available in the system, the target languages for the translation.

After the two steps mentioned above, a generic user of the system will see, when visualizing the page, an option to translate it, by entering the translation mode typical of a CAT tool, in which the text is divided into segments to be translated, as

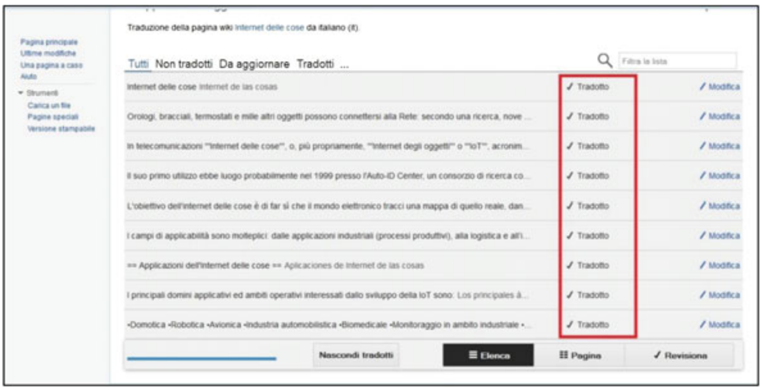

Fig. 2 A page divided into text segments to be translated; in the *red box,* we can see that all the segments have been translated (best viewed in colours)

shown in Fig. 45.2. In addition, the user can see a number of statistics about the state of translation tasks.

45.6 Collaborative Language Learning Using the WALLeT Platform

In this section, we describe our findings after a small-scale evaluation test based on a pilot project and then, we detail its future development we plan to do at large scale in the next academic year, i.e. starting from September 2015.

We tested the platform on a small case study involving ten Italian native language students divided into two groups of five each: one for the Spanish language and one for the English language. The main objectives of this pilot project were i) to help the Spanish and English teachers familiarize with the system and identify the necessary translation tasks to be performed in order to develop metalinguistic skills and ii) to test on a small scale the effectiveness of a collaborative learning approach deriving from the implementation and development of these second language learning activities within the MediaWiki platform. The students worked in a computer laboratory with one computer each and they were able to interact and coordinate during the different phases of the project exploiting the potentialities of the Wiki technology. The role of the teacher was to assist students who had been trained previously with a professional CAT tool (Trados) to manage translation tasks autonomously (basically focused on portions of English and Spanish literary and general texts). They were enhanced to reflect on some crucial aspects of a second language in particular on vocabulary idioms and lexical collocations. At the end of the project, students were requested to fill in a questionnaire aimed at evaluating both their language skills improvement and their learning experience.

From the students' perspective, the project is a success: the students enjoyed both the typology of tasks and their collaborative aspects, and all of them reported that the experience was engaging and interesting. Collaboration amongst peers, in fact, enables learners to perform deeper managing and processing of language material [13] since it leads to an increase in attentive resources when aiming at exploiting, for instance, problem-solving, decision-making, and critical thinking tasks [21, 29, 30].

On the other hand, i.e. from the teacher's perspective, we have to report mixed feelings: both teachers agreed that whilst the success of the system amongst the students is definitely an indication that we need to use this system on a larger scale, the platform currently lacks some automatisms to simplify the creation of translation tasks for the students: the text to be translated has to be split into pages manually by the teachers, who insert it in the system and then have to perform the two steps described in the previous section, to mark it for the translation.

We plan to do a large-scale project in the next 15 months, with approximately 200 Italian native students, mostly enroled in the *Languages in the Information Society* Degree and divided almost equally into two university courses, English and

Spanish. We are developing a (simple) extension of the MediaWiki platform, in order to help teachers with the insertion of the text to be translated and to be assigned to students. Details of this extension, together with the information on how to install and configure the whole WALLeT platform, can be found at the URL www.dis.uniroma1.it/~laura/WALLeT. We will divide the project into two phases, to be carried out, respectively, in either of the two academic terms: in the autumn–winter term, we plan to simply extend the small-scale evaluation to these students, by dividing them in small groups (i.e. 4–6 people in each group) where, before assigning them translation tasks, each group will be assessed in terms of second language needs and skills. In the second part (spring term), we plan to change the translation task and focus on the development of field-specific translation memories. As stated in the introduction, different specialized fields will be the domains of the lexical and terminological analysis. Students will be involved collaboratively in the construction of specialized corpora to be utilized and embedded in the new platform as translation memories.

In the light of recent developments in the literature on needs analysis [2], a first step will consist in providing learners with the necessary scaffolding for reflexivity on their needs in relation to the requirements of target disciplinary/professional communities. This will entail a reflection on genres features, focussing on the rhetorical moves and steps [3] and the related linguistic features mainly phraseology and syntactic preferences limited to a selection of genres (the more standardized, the better) from different specialized domains. Following this first step, a needs analysis questionnaire will be administered to the participants associated with translation activities, to let them experience the gap between their necessities and what they currently "lack" [15]. These data will be used, together with teachers' knowledge about the genre and insights from professional community informants for the preparation of teaching activities.

45.7 Conclusions

In this paper, we have presented a social collaborative learning platform, based on the popular MediaWiki platform and its Translate extension. We successfully tested the platform on a small scale and are now ready to start a more realistic study involving more than 200 students, enroled in the *Languages in the Information Society* Degree and divided into two university courses, English and Spanish.

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Chapter 46
Integrating Rich Learning Applications in LMS

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Abstract Currently, a learning management system (LMS) plays a central role in any e-learning environment. These environments include systems to handle the pedagogic aspects of the teaching–learning process (e.g. specialized tutors, simulation games) and the academic aspects (e.g. academic management systems). Thus, the potential for interoperability is an important, although over looked, aspect of an LMS. In this paper, we make a comparative study of the interoperability level of the most relevant LMS. We start by defining an application and a specification model. For the application model, we create a basic application that acts as a tool provider for LMS integration. The specification model acts as the API that the LMS should implement to communicate with the tool provider. Based on researches, we select the Learning Tools Interoperability (LTI) from IMS. Finally, we compare the LMS interoperability level defined as the effort made to integrate the application on the study LMS.

Keywords LMS · E-learning · Interoperability · Standards

46.1 Introduction

Interoperability is the ability of different computer systems, applications or services to communicate, share and exchange data, information and knowledge in a precise, effective and consistent way [1]. In the e-learning realm, interoperability is one of

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the most important aspects during the construction of an e-learning environment. Usually, system designers identify the environment requirements and select the tools needed to achieve the proposed objectives. However, many times it is forgotten that environmental tools may need to interact with each other due to several reasons such as implement a single sign-on system (SSO), harvest Open Archives Initiative Protocol for Metadata Harvesting (OAI-PMH) from digital repositories or, even, personalize the frontend graphical interface with data from a recommendation service.

Nowadays, a learning environment includes a plethora of systems and services that need to communicate to fulfil goals. One of the most important and central systems are the learning management system (LMS). Still, the LMS cannot afford to be isolated from other systems in an educational institution. Thus, the potential for interoperability is an important, although frequently overlooked, aspect of an LMS [2].

In this paper, we make a comparative study of the interoperability level of the most relevant LMS. This study is part of an effort to select an LMS on which to base the development of an e-learning environment for the teaching–learning process on the computer programming domain. We chose several LMSs vendors that combined have a significant share of the LMS market. We analyse and validate the interoperability features of these LMSs based on two models: specification and application models. The former presents the Learning Tools Interoperability (LTI) specification defined as an API for the standardization of the communication of LMS with external applications. The latter provides the guidelines for the integration of an external application using the specification model. In the final section, we draw conclusions on the results of this study.

46.2 The Specification Model

A common interoperability standard that is increasingly supported by major LMS vendors is the IMS LTI specification. The IMS LTI provides a uniform standard-based extension point, allowing remote tools and content to be integrated into LMSs. The main goal of LTI is to standardize the process of building links between learning tools and the LMS. There are several benefits from using this approach: educational institutions, LMS vendors and tool providers by adhering to a clearly defined interface between the LMS and the tool will decrease costs, increase options for students and instructors when selecting learning applications and also potentiate the use of software as a service (SaaS). The LTI has 3 key concepts [3]: the Tool Provider, the Tool Consumer and the Tool Profile.

The tool provider (TP) is a learning application that runs in a container separated from the LMS. It publishes one or more tools through tool profiles. A tool profile is an XML document describing how a tool integrates with a tool consumer. It contains tool metadata, vendor information, resource and event handlers and menu links. The tool consumer (FC) publishes a Tool Consumer Profile (XML descriptor of the Tool Consumer's supported LTI functionality that is read by the Tool Provider during deployment), provides a Tool Proxy Runtime and exposes the LTI services.

A subset of the full LTI v1.0 specification called IMS Basic LTI exposes a single (but limited) connection between the LMS and the tool provider. In particular, there is no provision for accessing run-time services in the LMS and only one security policy (OAuth protocol) is supported. For instance, to export content from Moodle to Mahara using the Basic LTI, the teacher (or LMS administrator) must first configure the tool (Mahara) as a Basic LTI tool in the course structure. When a student selects this tool, Moodle launches a Mahara session for the student. The Web interface for this session can either be embedded in Moodle's Web interface as an iframe or launched in a new browser window.

In March 2012, IMS launched the LTI v1.1 (final version) merging both specifications (Basic LTI and LTI). This version includes updates and clarifications as well as support for an outcomes service and bidirectional communication support. This version also includes the support for an outcomes service based on a subset of the IMS Learning Information Services (LIS)—the LTI Basic Outcomes Service.

The LIS specification is the definition of how systems manage the exchange of information that describes people, groups, memberships, courses and outcomes within the context of learning. Figure 46.1 shows how the bidirectionality of the LTI specification is performed. The TC provides launch data with LIS pointers to the TP. It is not required for the TC to provide these services. The LIS services could even be provided by a third system such as a student information system. Then, the TP calls the LTI Basic Outcomes Service if available. The service supports setting, retrieving and deleting LIS results associated with a particular user/resource combination. The following functions are supported:

- The replaceResultRequest sets a numeric grade (0.0–1.0) for a particular result;
- The readResultRequest function returns the current grade for a particular result;
- The deleteResultRequest function deletes the grade for a particular result.

LTI v2 has been under development for several years, and, in July 2013, the CC/LTI APMG approved a revision to the LTI v2 Public Draft and replaced the

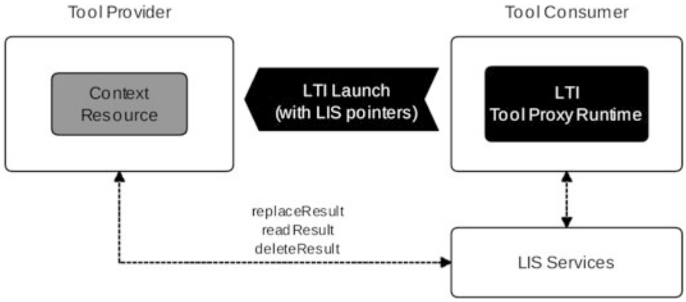

Fig. 46.1 Specification model based on IMS LTI

early public draft released in November 2012. The LTI 2.0 supports two types of connection defined between the Tool Consumer and the Tool Provider: message-based and service-based. A message-based connection involves the user with data being transferred as a signed HTTP POST request via their browser.

46.3 The Application Model

The application model defines the guidelines for the integration of an external application (tool provider) with an LMS (tool consumer). The integration relies on the LTI specification. The LTI specification recommends REST as the Web service flavour for exchanging data between the LMS and external tools. The LTI functions are summarized in Table 46.1.

The `Launch` function allows the execution of a particular external application within the LMS. Before launching, two steps are required: 1) the teacher (or LMS administrator) should configure the application as an external tool in the LMS control panel by setting the name and the URL of the application and 2) the teacher should add an activity into the course structure referring to the external tool. Later on, when a student selects the external tool, the LMS uses the URL to launch the external application through an HTTP POST. This request includes a set of launch parameters (LTI PARAMETERS) as hidden form fields.

Listing 1 shows a subset of the launch parameters that the LMS (Tool Consumer) sends to the external application (Tool Provider).

```
resource_link_id = 2
resource_link_title = MathGamify
lis_person_name_full = Silva Rui
lis_result_sourceid = {"data":{"iid":"1","userid":"2"}}
lis_outcome_service_url=http://server:8080/service.php
custom_game_level = 3
```

Table 46.1 also refers to three functions included in the IMS LIS Outcomes Service. These functions use the `lis_result_sourceid` parameter included in the launch request that is unique for every combination of `resource_link_id`/`user_id` parameters and identifies a unique row and column within the TC gradebook. After computing a grade, the external application calls the LTI Basic

Table 46.1 LTI functions

Function	REST
Launch	POST APP_URL < LTI_PARAMETERS
ReplaceResult	POST LIS_OUTCOMES_URL < LIS_SOURCE_ID + GRADE
ReadResult	POST LIS_OUTCOMES_URL < LIS_SOURCE_ID > GRADE
DeleteResult	POST LIS_OUTCOMES_URL < LIS_SOURCE_ID

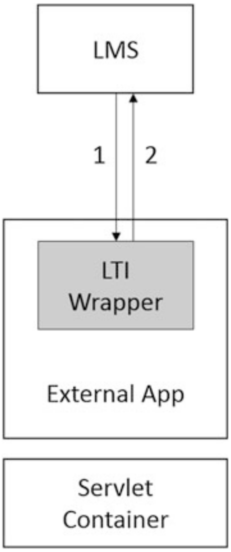

Fig. 46.2 Application model based on the LTI Wrapper

Outcomes Service using the URL stated in the `lis_outcome_service` URL launch parameter.

One of the key components of this integration is the LTI Wrapper (created by the authors) that implements both sides of the LTI communication. This component receives LTI requests from LMS and issues LTI requests to LMS. This Java package can be used by any application requiring LTI communication [4]. Figure 46.2 shows the architecture of the application model.

A typical use case starts with a HTTP message replied by the LMS to the student's browser that starts an LTI request processed by the LTI Wrapper (1). This request starts the external application (e.g. a course) on the browser where the students interact with the system. Finally, the results obtained by the student in the course are reported to the LMS using LTI (2).

46.4 Validation

In this section, we evaluate the previous models with seven LMSs. For this validation, a minimal external application was created—a simple multiplication game called MathGamify. This game can be used by primary school children to learn multiplication tables. MathGamify generates two random numbers. The first number is between 1 and the current game level and the second number is between 1 and 10. Then, the student/player has the opportunity to answer the multiplication value of the two numbers. The score is accumulated in the ratio of the player's level until player misses, in which case the score is reset to zero. The game was tested in seven LMSs. The results are presented in Table 46.2. Despite the support of the LTI

Table 46.2 LMS interoperability comparative study

LMS	Specification model	Application model
Moodle	YES	YES
Blackboard	YES	YES*
Sakai	YES	YES
Dokeos	NO	NO
Desire2Learn	YES	NO
eFront	NO	NO
ATutor	YES	NO

specification by several LMSs, only Moodle and Sakai successfully ran the MathGamify game. The Blackboard LMS (*) was able to launch the external game, but the grade results were not received with success.

46.5 Conclusion

This paper presents a study on the LMS interoperability. We defined two models to base the study: the specification model defines the communication specification that LMS should support to interact with external applications. Based on previous studies, the LTI specification was chosen; the application model presents the architecture environment for the integration of external applications. The integration is managed by a LTI Wrapper that encapsulates the complexity of the LTI API.

Based on the models, seven LMSs were chosen and validated through the integration of a LTI compatible game. Although the majority of the LMS supports LTI, only Moodle and Sakai were able to communicate with the game and get the grade results.

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Chapter 47
Three Uses of the Online Social Programming Training System: On Nature and Purpose of Spreading Algorithmic Problem Solving

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Abstract We report on experience related to the online training for the Italian and International Olympiads in Informatics (IOI). We developed an interactive online system, integrating the programming problems and the grading system used in several major programming contests, including the IOI. The system has been used in three distinct contexts: training students for the Italian Olympiads in Informatics (OII), training teachers in order to be able to assist students for the OII, and training

The title is a tribute to David Mamet's book *Three Uses of the Knife: On the Nature and Purpose of Drama.*

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the Italian team for the IOI. We also present the initial design of an extension deemed to provide trainees with a personalized support to skills' enhancement on contest problems.

47.1 Introduction

The International Olympiads in Informatics (IOI) is an annual programming competition for secondary school students patronized by UNESCO. First IOI has been started in Bulgaria in 1989. The 2014 IOI, held in Taiwan, Taipei, saw participation by 84 countries and 311 contestants (each country can have up to four contestants). Participants are usually the winners of national competitions.

Here, we first introduce `oii-web`, an interactive online training platform, based on the *contest management system* (CMS, http://cms-dev.github.io/ [9, 10]), which is the grading system used in several programming competitions, including IOI. We built, around `oii-web`, three distinct, in both target audience and functionalities, Web-based platforms: one dedicated to students preparing for the Italian Olympiads in Informatics (OII), one for the teachers, with a complete course on programming and several resources available, and the third to support the selection and the training of the Italian team for the IOI. We believe that our online training system fills a gap, since there are several open source grading systems and several online training platforms, but to the best of our knowledge, there is no open source solution if one wants to host his own training platform. We report on our experience with the three platforms, designed around the common core, `oii-web`, that allows to navigate through problems, propose solutions, and get feedback about it. The overall system is already apt to be fruitfully used, with educational aims, as a tool for competitive programing. Yet we are pursuing its enrichment with aspects of personalization to trainees characteristics and needs, aiming to better help them enhance their abilities to deal with contest problems: This would be novel, to our knowledge. So, in the last part of the paper, we discuss the requirements of such extension showing an initial modeling schema for problems, solutions, and ultimately trainees.

47.2 Related Work

Here, we deal with various topics connected to programming competitions and, more generally, computer programming learning for secondary school students: a Web training platform, the organization of national olympiads in informatics, and our experience in broadening the participation to it.

On these topics, a crucial information source is the *Olympiads in Informatics* journal, founded in 2007, providing "*an international forum for presenting* *research and developments in the specific scope of teaching and learning informatics through olympiads and other competitions.*" Books such as [5, 12] provide also essential material about algorithms, data structures, and heuristics needed in programming contests.

The importance and the effectiveness of programming contests in learning programming and, more generally, computer science have been observed and emphasized greatly in the literature: We mention the works of Dagienė [3] and Garcia-Mateos and Fernandez-Aleman [4].

Various kinds of automated support to programming education are met in research since decades. The widest area of investigation seems to be related to introductory programming courses, where students learn to write programs, according to a programming language syntax and semantics, and to solve problems. In this way, students are trained on both basic algorithms and their coding. Programming errors are spotted basically in two phases: Syntactic/static semantic errors are pointed out by the compiler, while logic/dynamic semantic errors are spotted by testing. So, program assessment is usually based on

- *Static analysis*, which gathers information about the program and produces feedback without execution. In this family fall approaches based on compiler error detection and explanation [6, 14], structured similarity between marked and unmarked programs [11], and also non-structural analysis, keyword search, and plagiarism detection [7].
- *Dynamic analysis*, which tests the program on accurately chosen input datasets and compares actual and expected output. One important application of this program analysis is in competitive learning tools, used to manage programming contests, such as [8].

Wang et al. [13] combine the two approaches: First, the program undergoes static analysis, to check compilation errors and similarity with "model programs." Then, a dynamic testing is performed, and possibly, the program adds to model programs.

Grading systems such as CMS are mainly based on dynamic testing and are many: Among them are those used in ACM International Collegiate Programming Contest (ICPC), i.e., the proprietary Kattis,[1] and the open source PC^2, available at http://pc2.ecs.csus.edu/. Other open source grading systems are Open Judge System[2] and DOMJudge.[3]

If we focus on online training platforms, among several high-quality ones are UVa Online Judge[4] and the more recent Sphere Online Judge[5] (SPOJ). Besides these training platforms, there are several well-known programming contest platforms,

[1]https://kth.kattis.com/.

[2]https://github.com/NikolayIT/OpenJudgeSystem.

[3]http://www.domjudge.org/.

[4]https://uva.onlinejudge.org/.

[5]http://www.spoj.com/.

including Codeforces, USACO, COCI, TopCoder, CodeChef, and HackerEarth, which run contests with different periodicities. There are also events based on programming contests, such as the Google Code Jam and the Facebook Hacker Cup. A detailed survey of programming contests is in [2].

47.3 Olympiads in Informatics

The IOI started in Bulgaria in 1989, patronized by UNESCO. They are considered one of the most important programming competitions in the world. Each country can have four contestants, and the competition is divided into two days. On each day, contestants will be given three tasks to complete in 5 h. Each task is worth 100 points and, since IOI 2010, is divided into subtasks, each worth a portion of the total points. There are time and memory limits for each subtask, and points are awarded only when all the tests in subtask yield correct results within the limits. There are also interactive tasks, such as games, in which the contestant code alternates moves against an adversary.

In Fig. 47.1, we can see a graphical representation of a task, taken from OII 2014 final. The task, `taglialegna` (lumberjack), can be summarized in the following way: *There is a line of trees, with one meter of space between each of them. Each tree has a known height, in meters, and you can cut it aiming it toward its right or left. When an m meter tree falls, like in a domino game, it forces the falling of its* $m - 1$ *close trees, and this in turn can force other trees to fall. You can decide which tree to cut, and for each of them, you can choose in which direction it will fall. What is the minimum number of trees to cut in order to remove all the trees in the line?* For this task, the subtasks were designed to distinguish algorithms of different computational costs: If we denote with n the number of trees in the line, all the points were awarded to a (definitely not trivial) $O(n)$ solution, achieved by only one contestant, and decreasing points were assigned, respectively, to $O(n \log n)$, $O(n^2)$, and $O(n^3)$ solutions.

Italy participated in IOI for the first time in 2000, and since 2001, it started a national competition, promoted by a joint effort of Ministry of Education, University and Research (MIUR) and Italian Association for Informatics and

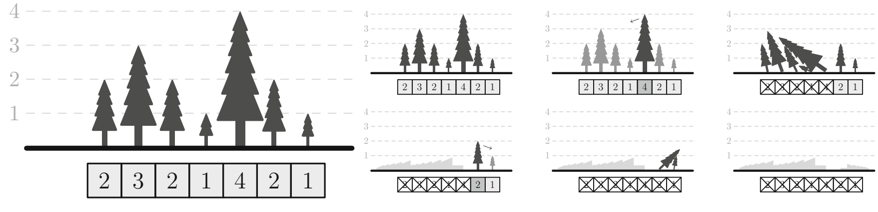

Fig. 47.1 The graphical representation of the task `taglialegna` (lumberjack), from OII 2014 final: an input instance (*left*) and a possible solution that uses two cuts (*right*)

Automatic Calculus (AICA), a nonprofit organization . The OII is divided into three phases:

1. **First Selection (Schools, November)**: In this phase, in their own schools, approximately 20k students compete to solve, on paper, a test that involves math, logic, and programming abilities; in particular, there are some fragments of code (C/C++ or Pascal), and the students are asked to understand the behavior of the fragments.
2. **Second Selection (Regions, April)**: In this phase, there are approximately 40 venues, where approximately 1200 students, selected from the previous phase, compete by solving three programming tasks on the computer. In this phase, points are awarded for solving the tasks, independently from the complexity of the solution.
3. **Third Selection (National Final, September)**: Approximately 100 students are asked to solve *efficiently* three programming tasks on the computer. They compete for 5 gold, 10 silver, and 20 bronze medals.

From the above description, it should be clear that the difference in programming abilities is required: We first ask students to be able to *read* code, then to *write* code, and finally to *efficiently write code*. A more detailed picture of the OII organization is described in [1].

The selection process does not end with the national final: The gold and silver medal winners, together with at most five bronze medal winners, selected by (young) age, form the group of IOI candidates, and four of them will represent Italy in the next IOI (usually held in July or August). Thus, there is almost one year to train and select them, and this process is mainly done in four stages held nearby Volterra. In each of the stages, there are theoretical lessons, ranging from traditional algorithms and data structures to competitive programming tips and tricks, as well as programming contests. Besides the stages, there is a continuous online support for self-improvement: The IOI candidates are assisted by tutors (former IOI contestants) for assistance and guidance, and several training contests are organized, some of which focused on specific topics.

47.4 The Online Training System: `oii-web`

Our online training platform, `oii-web`, is based on the *contest management system* (CMS) [9, 10], the grading system used in several programming competitions, including IOI. CMS was designed and coded almost exclusively by three developers involved in the OII: Italy hosted IOI 2012, and therefore, since 2010, it started the development of CMS, which was used/tested in the OII finals 2011 and, few months later, was the grading system of IOI 2012. CMS version 1.0 was released in March 2013 and since then has been used in both IOI 2013 and IOI 2014, together with several other programming competitions in the world [10].

We began the development of `oii-web` during the preparation of the IOI candidates for IOI 2012: Why did we need an online training platform? The short answer is: In a programming competition, there are very few (usually from 3 to 7) problems, to be solved in a short frame of time; in order to train the IOI candidates, we needed a system that allowed us to give them more problems they can solve whenever they want, so the first version of `oii-web` was simply an instance of CMS with one competition running, with several problems and unlimited time for training the IOI candidates and, later, the two[6] Italian teams competing in IOI 2012.

Later, we started using it consistently, and our feature list was growing almost daily, both for the front end and for the back end of the system:

1. It would be nice to provide some information about each problem, so the student can choose it without reading the whole description.
2. It would be nice to have a way to exchange messages, so students and tutors can chat about the problems.
3. It would be nice to have a way to show/hide problems, so we can use some of them in contests to rank the students.
4. It would be nice to have stats about each problem and who was able to solve it (in a grading system, there are these stats but not visible to contestants).

Thus, we decide to include all these above-mentioned features, together with others, and build an online grading system, `oii-web`. We integrated the open source *Discourse*[7] to provide forum functionalities. The source code of the system is freely available[8] in GitHub and it is released under the GNU Affero General Public License.[9] Furthermore, it is also available[10] as a "Dockerized" app for docker,[11] an open platform to build, ship, and run distributed applications.

47.5 The Three Platforms

In this section, we briefly describe the three platforms, based on `oii-web`, we developed and their differences.

OII training is the platform devoted to the students that are interested in OII. In this platform, there are approximately 180 problems spanning several techniques and difficulties, ranging from regional contests to IOI level. Furthermore, there are also the tests, from the first selection of OII (schools' selection), available as

[6]The nation that hosts IOI can have two teams of four elements, but only one team is eligible for medals.

[7]www.discourse.com.

[8]https://github.com/veluca93/oii-web/.

[9]http://www.gnu.org/licenses/agpl.

[10]https://registry.hub.docker.com/u/veluca93/oii-web/.

[11]www.docker.com.

interactive online forms. So far, we did not advertise this platform in the schools, since we consider it in a beta-testing phase. We allowed students to register freely, and so far, we have approximately 500 users despite the lack of promotion.

DIGIT is the platform dedicated to teachers: We realized this platform in a project sponsored by the MIUR, where the aim was to build a self-paced online course of computer programming, focused on the olympiads in informatics. The idea was to train the teachers, so they would have been able to train their students. Thus, this platform is currently the richest of the three, in terms of contents and functionalities. There are video courses of C/C++ and Pascal programming, algorithms and data structures, and some basic video tutorial as well including how to use the platform to submit a solution. There are also some lecture notes, and all the materials can be distributed to students as well; the video lectures are also available on the OII channel on YouTube. The MIUR used this platform, since October 2013, in three distinct courses, with a fourth one scheduled to start in September 2015. So far, approximately 2000 teachers followed this course, and the effects on the OII were impressive: The participation of students in OII preliminary stages raised from 13k to 21k.

IOI candidates is the last platform, and the only one not publicly available, since it is devoted to the IOI candidates. This platform, as we mentioned before, has been the original motivation to develop the whole `oii-web system`. This platform has all the problems available to the other two platforms, together with a *reserved* set of problems that we use in the contests to rank the students. The students are asked not to discuss these problems in public forum or social network, since we usually reuse them after few years.

47.6 Our Experience

The advantages of a training system are clear: Without it, we need to give students, besides the text of the problem, the input cases, the rules for counting the points, and, in some cases,[12] a code to check the correctness of the produced output. And the student has to run its code against every input, run the checker against each input and matching output, and check the time and memory limits that can be a cumbersome operation for a beginner. Furthermore, even if we automatize this task, for example, by a script given to the student, there is still the problem of measuring the running times in different machines: Students can have very different hardware and it is meaningless to state time limits without knowing their hardware.

[12]To check the correctness of some problems is enough to check that the output produced by the student is the same as the output produced by the correct solution; in other cases, usually when there is more than a unique solution for a problem, like finding a path in a graph under some constraint, it is necessary to write a checker code that verifies the solution proposed for the given input.

Our path began, as we mentioned before, with the needs of a training system able to assist us with the preparation of Italian IOI candidates. We soon realized the advantages of such a system, as opposed to the use of an online platform like UVa Online Judge: We simply had more control, and this leads to a more effective teaching experience. We almost immediately decided to develop an online platform for the OII students as well, and we enriched our basic system with more features, in order to be able to deal with a much larger number of (averagely) less motivated students. In the beginning of 2013, the OII training platform went online, in the form of a publicly available beta, as we were planning to add more features to make it more appealing for a larger audience. Almost concurrently, the MIUR asked us to design an online course for teachers, and we immediately decided to build it around our platform. So, in the next months, we adapted the system for the DIGIT platform and realized the video lectures; in October 2013, we launched the first course: The MIUR opened a call for 250 teachers to be freely allowed to follow the course. The call was supposed to stay open for ten days, but we reached 250 teachers in the first day, and we decided to admit more. In subsequent courses, since we observed that the server was working fine, we raised the number of teachers per course to 700. At the end of each course, there is a programming contest, and the ones that perform above threshold (solving three problems out of seven) are awarded with a certification. Note that once a teacher has access to the platform, he is allowed to use it also after the end of the course. Many teachers reported us that they had fun using the platform and that they plan to keep on using it. Also, new video lectures are added to each edition of the course.

Our experience shows that the engagement in having or not a training system is completely different: We witnessed this at all the learners' levels; beginners were more involved, and advanced learners often joined the developers' community (mostly made of tutors and former IOI contestants) either to contribute to the system development or to propose new problems. The teachers were incredibly active in the forum, exchanging tips and solution strategies as well as mutual support. The IOI candidates are literally eager to contribute to the system or to propose design of new problems, maybe because they see the tutors as a model, or simply because they enjoy it so much that they want to be part of it.

47.7 Further Developments

A work of Wang et al. [13] states the following requirements for a comprehensive program assessment system: (1) *sufficiently extended testing*, so as to cover the various cases of computation; (2) *checking on the program structure*, to see that the problem specification is met, and no cunning shortcuts bring to the correct output; (3) *accepting and reasonably assessing programs with static errors*; and (4) *providing immediate and correcting feedback*.

We think that the developments in the `oii-web` system should ultimately fulfill these requirements, while the present directions should deal closely with the present purposes of the system, that is, to allow non-novice students to train for the contests. So here, we try and define a model to support

- a static analysis stage where solution strategies (algorithm, data structure, and their mutual feasibility) rather than syntactic/semantic errors are considered,
- an interactive communication between system and student, to help
  - develop one's capability to select solution strategies, by giving feedback on the actual choice, and
  - plan a path of growth of one's skills, by suggesting about next suitable problems to undertake.
- (and dynamic testing in the usual form, as it is already done).

Problems (the exercises proposed in the various contests, yearly), *Solution*s (the programs proposed by the students), and ultimately the *Student*s are modeled based on a tagging mechanism. Tags are the names of problems (*P*), the algorithms (A) and data structures (DS) usable and/or used in the solutions (*S*) of problems, the contests (C), and the levels of confidence (L) in the use of combinations of As and DSs.

Teachers in charge of the organization of a contest are named *guru*s; students that came out to be "exemplary" in a contest, and so "whose choices can count" when a solution to a problem is to be assessed, are called EPs. EPs can be promoted as guru.

A problem is modeled as a family of strategy choices (A and DS), suitable for its solution. Differences in that suitability can be pointed out by a weight. The weight is computed based on the frequency of that A/DS chosen and on the reputation of who performed that choice in the related contest. Notice that the reputation of t gurus and EPs is contextualized to the contest.

$$P = \{\langle \mathrm{A}, \mathrm{DS}, \mathrm{weight}, \mathrm{contest} \rangle\}$$

A solution submitted by a student is modeled by the strategy chosen for it: S = {⟨person, P, A, DS, conteXt⟩}, where conteXt is either a contest name or "training" (off contest).

This metadata is provided by the student, in order to allow for a timely feedback from the dynamic analysis. On the other hand, that metadata might be inaccurate, so it is subject to scrutiny: When a check points out that the data were wrong, it is changed accordingly, or (in the extreme case) the solution is removed altogether.

This check is done by gurus. A more social kind of scrutiny has been devised, yet it cannot be applied, as the students' solutions submitted to the system are not to be shown in public, at least for the time being.

The submitted solution is statically checked by comparing its specification S with that of the problem P. A feedback can be then given about the appropriateness of the choice, its present weight, and possible better-weighted alternatives.

The lightweight student model we can define in this framework defines the skills shown by the student while solving problems in the system; it is a collection of "acquirements," each one expressing the fact that a given problem has been solved, how, how well, and in what conteXt

$$\mathrm{SM(person)} = \{\langle \mathrm{P, A, DS, level, conteXt} \rangle\},$$

where *level* is a discrete variable in [1...5] associated with the outcome of the dynamic analysis of the solution (or solutions) submitted by the student on the problem.

The above modeling framework can be used during a contest, in order to collect problem models and data on students (for instance, to compute students' reputation and define the set of EPs for that contest).

However, here, we are also interested in the possible use of this framework in social Web-based settings, to foster training in view of a next contest. The CMS would be the place for such training, organized by the following protocol.

1. A *Target Skills* is given. This is a set of triples designating the aim of the training (at this stage for all the system): TS = {⟨A, DS, level⟩}
2. The trainee can access the set of problems available from the previous contest, his/her student model, and the TS.
3. While the trainee is entitled to select any problem and submit the related solution, the system can provide a list of suggestions, for "best next problems to undertake" in order to enhance SM (trainee) toward coverage of TS. This list is done by
   (a) defining the set of elements in TS that are close to be covered by tuples in SM (*proximal coverage*—PC);
   (b) defining a set of problems, whose undertaking can bring to add elements in PC to the student model.
4. Upon submission of a solution, the trainee provides its initial modeling (⟨A, DS⟩).
5. The dynamic analysis of the solution establishes the *level* value for the tuple ⟨P, A, DS, level, conteXt⟩ going to join the student model.

Notice that the trainee specification of the solution can be subject only to late evaluation (by guru), in order to allow for a timely feedback coming from the dynamic analysis. So the new element in the SM is *subjudice* and it could be modified or, in the extreme cases, deleted.

47.8 Conclusions

In this paper, we introduced `oii-web`, an online training system for programming contests. The system is based on CMS, the grading system used currently in IOI competitions and other programming contests as well. We developed three distinct platforms, based on `oii-web`, aimed at three distinct user sets: students enrolled in

OII, their teachers, and IOI candidates, i.e., the small set of students among which will be selected the four to represent Italy at IOI. We discussed briefly our experience, together with some current developments. We believe that as happened in our case, the use of such a system can contribute to spread the algorithmic problem-solving skills needed in programming contests.

We also believe that this tool can scale up toward being an educational support to refining students' skills in "algorithm mastery," and we have presented lines of development in that direction.

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Chapter 48
Semiautomatic Annotation of MOOC Forum Posts

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Abstract Massive online open courses' (MOOCs') students who use discussion forums have higher chances of finishing the course. However, little research has been conducted for understanding the underlying factors. One of the reasons which hinders the analysis is the amount of manual work required for annotating posts. In this paper, we use machine learning techniques to extrapolate small set of annotations to the whole forum. These annotations not only allow MOOC producers to summarize the state of the forum, but they also allow researchers to deeper understand the role of the forum in the learning process.

48.1 Introduction

One of the main differences between MOOCs and university courses is the limited social interactions. Researchers tried to investigate this component, suggesting, for example, MOOC study groups [2]. Nevertheless, for the moment, a forum remains the central channel of collaboration.

Forum activities positively correlate with grades and retention [3]. However, little research has been done to analyze these relations on a more granular level than active or passive activities. Deeper analysis requires tedious manual annotations, preferably done by several judges independently. From the research perspective, this significantly increases the cost of the analysis, whereas from practical perspective, in case of courses with thousands of users, it is not feasible to track all the post annotations dynamically during the course. We argue that recent machine learning improvements allow us to address this problem and benefit in both cases.

We distinguish two machine learning approaches to the problem: unsupervised and supervised learning. The unsupervised learning allows to group posts together

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according to imposed measures. Semantics of the groups are not determined by the algorithm and often they are difficult to interpret. Conversely, the supervised learning is based on ground truth—a set of posts annotated manually in which semantics are predefined. It allows us to extend known annotations to a larger set. Unsupervised techniques were recently successfully applied for clustering dialogues in MOOC forums [4]. In this study, we employ the supervised approach and refer to the technique as a *semiautomatic annotation*. We present the dataflow in Fig. 48.1.

Semiautomatic text classification was successfully used to analyze political forums [6] and technical forums [8, 9]. In addition, both written and spoken conversations were analyzed [7]. Although the latter is outside the context of our work, still the techniques prove to be universal.

The semiautomatic annotation can support the work of MOOC practitioners and other researchers. As an example application of our technique, we check to what extent we can identify threads important for the learning process. This could allow us, for example, to support teaching staff by alarming them about important questions, which have not yet been addressed. Another possible application is classification of users according to their behavior and investigating if certain activity patterns reflect their performance in the course.

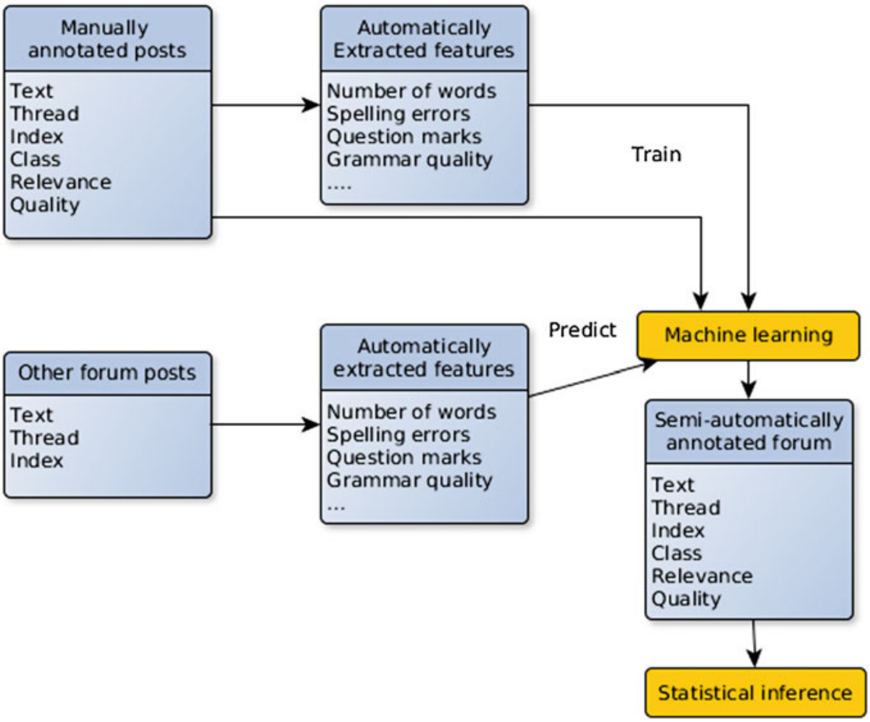

Fig. 48.1 Instead of manually annotating the whole forum, we annotate a small part and employ machine learning techniques. This allows us to draw conclusions from the whole annotated forum

Our techniques can also support practitioners in automatic assessment of measures already established in literature, which are costly to implement manually in practice. This includes scoring posts in discussion forums, based on the overall contribution of the post to the thread or subject [11, 12], supporting forum management [1], measuring emotional content of posts [10], or engagement of students [5]. Finally, annotations provide another dimension for the analysis of design choices and may extend the previous results of Coetzee et al. [3].

Contributions of this work are twofold. First, we suggest methodology for automatic annotation of forum posts, which can be beneficial for many MOOC stakeholders. Second, we use estimated annotations for large-scale analysis of performance of students participating in MOOC forums and we answer research questions: Do students who ask questions perform better than students who answer? To what extent the quality of the post reflects students' performance in the course? How can we support work of teaching assistants using automatic annotations?

48.2 Dataset

We analyze forum data from the Scala MOOC given by the EPFL in 2014. Our dataset consists of 4316 posts of 1336 different users. Apart from the content of the post, we also have the id of the thread, id of the author, time stamp of posting, position in the thread, and the title of the thread. In order to reduce the impact of the language factor, we only consider posts written in English. Moreover, we know the final grade of each user, or we have information that they dropped out.

48.3 Post Annotation

As we want to classify and compare forum behaviors, such as *student asking questions*, *student answering questions*, we suggest several **classes of posts**. We use classification scheme introduced by Sridhar et al. [6], altered for MOOC context. For possible values of this feature, we refer to Table 48.1.

Since one objective of automatic annotation in our study is the detection of important posts which were not yet properly addressed, we choose to assess the *importance* of the content in the relation with the course. To that end, we introduce two indicators: *Relevance* and *Comprehensibility*. These notions are subjective to this study and can be altered in other specific applications.

Relevance describes how closely related the content of the post is with the content of the course. We distinguish 5 levels of relevance:

1. *off-topic*—student has no intention to be even close to the content of the course,
2. *slightly irrelevant*—the relation is very superficial and main point of the post is off-topic,

Table 48.1 Post classes ordered according to their *importance* in the context of our study

Class	Description
Question	Requests of information about the course
Answer	Attempt to answer the question posed in the thread
Clarification request	Request for more details/clarifications concerning the solution
Clarification	Follow-up answer to the request or additional clarification to the answer even without the request
Positive feedback	Student's (not necessarily question author) positive feedback (gratitude, etc.)
Negative feedback	Student's negative feedback (solution does not work, have errors, etc.)
Off-task	Any form of spam or misplaced text, not relevant to the thread

If a post belongs to several classes at once, we classify it to a *more important* class

3. *neutral*—there is some relation to the topic, but vague and not clear,
4. *relevant*—there is a clear intention to understand/solve some problem,
5. *highly relevant*—the student demonstrates understanding and his own tries to solve the problem.

The relevance varies only for three post classes: *question*, *answer,* and *clarification*. In other cases, the relevance is implicit, for example, *off-task* posts are *off-topic* and there is no room for variability prediction.

Comprehensibility expresses how easily readable is the post. We consider three levels of this feature:

1. *misleading*—unclear or misleading language, where it is not clear what is the message,
2. *neutral*—clear and accurate statement,
3. *high comprehensibility*—student states all the necessarily details of the problems and/or his own attempts to the solution.

48.4 Automatic Annotation

Our goal is to predict variables introduced in Sect. 48.3, given a small set of manual annotations. To this end, we automatically extract features presented in Table 48.2 from the content of the forum and use machine learning techniques which were trained on the manually annotated dataset. A set of *relevant words* was determined from the content of lecture slides and posts, manually by listing words which appear the most often and extracting those which are specific to the course. These words were used for `RelWords*` features. `GrammarQuality`, `ErrSpell`, and `ErrGram` were automatically extracted using `R` text mining `tm` package.

The basic set of features from Table 48.2 can be still extended in order to achieve more accurate classification; however, in the context of our research questions the results were already satisfying.

Table 48.2 Features extracted from the posts

Name	Description
NumWords	Number of words
RelWords	Number of relevant words
RelWordsRatio	Ratio of relevant words
NumSent	Number of sentences
ErrSpell	Number of spelling errors
ErrGram	Number of grammar errors
NumQMarks	Number of question marks
Index	Index in the thread (1—for the first post in the thread)
NumWordsTitle	Words in the thread title
RelWordsTitle	Relevant words in the thread title
RelWordsTitleRatio	Ratio of relevant words in the title
GrammarQuality	Correctness of grammar (1–10)

The extracted features were used for training machine learning algorithms using `R` package `CARET`. As the training set, we use 100 randomly selected posts, annotated manually by one student. This annotation introduces additional error; however, for the purpose of this study we treat these annotations as the ground truth.

48.4.1 Measures of Accuracy

In the classification of posts, we measure accuracy of prediction by out-sample Cohen's κ. For relevance and comprehensibility, since both indicators can be treated as ordinal, we will use regression models to predict the values. We measure accuracy of these models by root-mean-squared error (RMSE). For example, for relevance prediction, we define

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} \left\| R_j - \hat{R}_j \right\|^2},$$

where R_j is the relevance of the jth post, $\hat{R}_j$ is the predicted relevance, and n is the number of posts. RMSE approximates average deviation of prediction from the observed value.

Both measures were estimated by cross-validation. In each case, we repeated the following procedure 5 times: We take randomly 80 % of the training observations, we predict remaining 20 % and we compute the measure. The average of 5 measurements serves as the estimator of the measure.

Table 48.3 Cohen's κ of various methods used for classification

Method	Cohen's κ
SVM	0.42
Bayesian model	0.40
Logistic regression	0.35
Random forests	0.57

The larger the better

Table 48.4 RMSE of regression of relevance and comprehensibility using various methods

Method	Relevance	Comprehensibility
Linear regression	0.98	0.58
Penalized linear regression	0.98	0.54
Neural network	1.03	0.69
SVM	0.96	0.56

48.4.2 Results of the Semiautomatic Annotation

In classification task, we implement several machine learning methods including *multiclass logistic regression*, *Bayesian Model*, *random forest model*, *support vector machine* along with *kernel method* to maximize Cohen's κ, and we find that *random forest by randomization* performs the best in our context, with $\kappa = 0.57$.

We use the 10 extracted features to predict the *Relevance* and take root-mean-squared error (RMSE) as a measure of accuracy. After testing several regression methods, we employ *SVM with linear kernel* which yields the lowest RMSE equals 0.96. Finally, in the same way we predict *Comprehensibility*; in this case, we chose *penalized linear regression* as the most efficient method, giving RMSE is around 0.54. Other values are presented in Tables 48.3 and 48.4.

48.5 Applications of Annotations

In this section, we discuss possible applications of semiautomated annotator, both for practitioners and for researchers. First, the direct application is the prediction of *important* posts, where, for, importance is defined by relevance to the subject and high comprehensibility. Teaching assistants, instead of reading posts one by one, could generate a list of important posts which have not yet been answered. Second, we can analyze performance of students with certain posting patterns. In this section, we report the latter analysis.

We investigate if students who ask more questions achieve better results than those who answer more questions. To this end, we compare two subgroups of students, those whose questions account for more than 80 % of their posts, those whose answers account for more than 80 % of their posts. We find that students who answer more questions perform better than those who ask more questions ($T = -4.9829$, $df = 541$, $p < 0.01$), as depicted in Fig. 48.2.

We also analyze the *Relevance* of posts as a predictor of students' performance. Hence, we also set two groups of students, the first group consists of students with average relevance above 4 and the second group consists of students with average relevance below 2. We compare distributions of the results within these two groups of students and present it in Fig. 48.3. As the Figure shows, the students with low relevance obtain much better performance than those with high relevance ($T = -5.6875$, $df = 146.35$, $p < 0.01$).

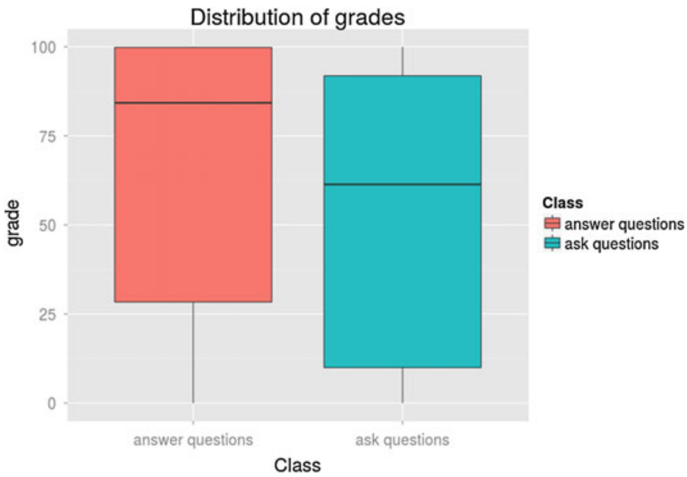

Fig. 48.2 Mean grades between students who ask more questions and answer more questions

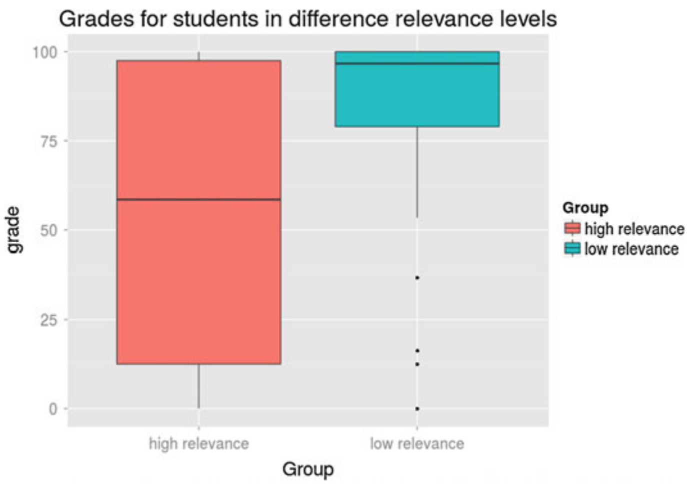

Fig. 48.3 Box plot of grades of students with different average relevance level

Note that we considered the extreme cases, i.e., relevance smaller than 2 or larger than 4. In case of more relaxed thresholds 2.5 and 3.5, the effect size is smaller but still significant at $\alpha = 0.05$.

As the result is very unintuitive, we analyze manually the posts which were predicted to be less relevant. We find that indeed these posts are not close to the content of this course. Instead, they often concern social interactions like finding friends. Questions concern, for example, nationality of other students ("*where are you from?*"). The posts which were predicted to be close to the content of the course are highly related to the lessons. This indicates that a variable explaining *social interactions* could be a good indicator of performance. In future studies, we suggest emphasizing this social aspect instead of *low relevance*, leading to more intuitive interpretation.

For finding the relation between *Comprehensibility* and the final grades, we divide students into different levels of average post comprehensibility. We define low comprehensibility as lower than 1.5 and high comprehensibility as larger than 2.5. Although the results of students with high comprehensibility posts may appear to have smaller variance in Fig. 48.4, there is no statistical evidence for such claim ($F = 1.222$, d$f = 163$, $p = 0.3575$). Moreover, the mean grades in these two groups are not significantly different.

Deeper investigation of Comprehensibility indicator reveals that our notion of *Comprehensibility* is not relevant in the context of programming courses, particularly because posts containing chunks of source code are classified as low comprehensibility, whereas in the context of programming this code substantially improves readability. This problem can be solved by introducing features based on the detected source code, as well as ground truth according to which posts with code are classified higher.

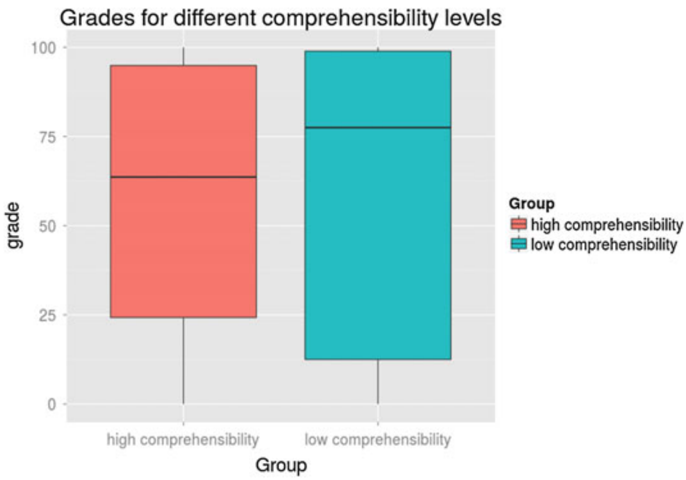

Fig. 48.4 Box plot of grades of students with different average comprehensibility levels

Other low comprehensibility posts are those with very short sentences, just one or two words in each post. Capturing the variability of these short posts may require techniques beyond the introduced framework. Note that in our analysis, we rely on the assumption that posts treated as independent entities contain information sufficient for classification and regression. However, a post containing only “No” is very strongly context-dependent. Depending on the task, we can either remove these posts from the analysis or seek for more complex models, which take into account correlations within a thread.

48.6 Limitations

Through the data analysis process, we found that the seven classes in our model do not cover all possible forum interactions. For example, some students just share their thoughts about the course and they do not ask any direct questions. This can be addressed by the introduction of additional classes.

The 10 features we extract directly from the posts are not enough for distinguishing some of the classes. For example, in our setup, *Clarification Request* and *Negative Feedback* have similar values of predictive features. Depending on the application, we could either join the classes to a general one or introduce more precise features, e.g., an indicator of phrases “doesn’t work,” “sorry,” etc.

Some students tend to cite the post before answering it. Posts of this kind may be misclassified as questions, while they are actually answers. Again, depending on the application and the forum structure, another predictive feature could be introduced.

Finally, posts were annotated just by one judge, and these annotations were taken as ground truth, which can lead to significant inaccuracy. Larger dataset of annotated post and annotation from independent judges would allow us to understand deeper technical aspects of the problem.

48.7 Conclusion

In this project, we used machine learning techniques to annotate posts and answer questions related to the users’ behavior in forum. We introduced a methodology which allows to answer research questions given only a limited number of annotations. We find that students who answer more questions achieve higher grades than those who ask more questions. Moreover, students who are more social in the MOOC performed better. We also find that the *Comprehensibility* measure, based merely on the elementary features and small set of annotations, should be altered for programming courses. This measure in conjunction with relevance can simplify the work of teaching assistants in a MOOC. Although our elementary methodology already yields satisfactory results, many improvements can be incorporated for specific applications of semiautomatic annotations.

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Chapter 49
Virtual Social Spaces for Practice and Experience Sharing

Eman AbuKhousa and Yacine Atif

Abstract Higher education learners are increasingly seeking educational experiences that are directly relevant to their professional interests and aspiration, especially, while aiming at career success and employability. This creates the need for practice-oriented learning approaches that focus on workforce skills. In this paper, we propose virtual social space structures which cluster learners into communities of practice (CoPs) to complement academic pathways with career-specific competencies' development. Clustering employs social learning analytics (SLA) techniques to predict group together similar career-aspiration patterns into CoPs, and to subsequently track domain-related practice acquisitions. Our approach considers both personal preferences and career predispositions of learners as they join CoPs and thrive throughout CoPs life cycle. We discuss our three-module model: (1) career readiness to assert general professional dispositions, (2) career prediction to identify a targeted domain of employment, and (3) a career development process to raise the skills that are relevant to the predicted domain of employment.

Keywords Virtual community of practice (CoP) · Social networks · Learning analytics · Career prediction · Fuzzy semi-supervised clustering

49.1 Introduction

Learners have become more aware of the job market needs and the pursuit of competitiveness; and so, they are increasingly seeking educational experiences that are directly relevant to their professional interests and objectives, especially, as relate to career success and employability. Higher education has traditionally been

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notorious for the inefficient use of data to improve the quality and the value of graduates in meeting market needs. Failure to utilize readily evident data and feedback on learning practices to meet market needs increases further the gap between education and industry and reduces intervention opportunities to prepare graduates for a successful career path and a superior professional performance. This has brought the attention to community of practice (CoP) as one of the most informal ways to shift current teaching and learning methods. View learning as the process of joining a CoP nurtures a new form of apprenticeship as students engage in "learning to be" even while they are mastering the skill of a field. CoP concept has actually gained momentum in different educational systems since the 1990s [1]. While with Internet introduction, virtual CoPs emerge as the twenty-first century method of learning to enhance educational programs and professional development [2]. To qualify as virtual CoP, it must include active members who share a specific domain of interest. Members must actively engage in a collective learning process within their domain through social structures that assist in knowledge creation and sharing.

In our proposed approach, we employ CoP model and SNs concepts to bridge the gap between higher education and industry by introducing a new online social structure made up of interconnected CoPs. This model then extends the perspective of educational institutions and develops a joint effort with the industry to leverage education and workforce developments. Learners are first assigned to dedicated CoPs within which they thrive collaboratively refining their interests and practice-related skills. This career development process evolves into a mentorship structure within CoPs. The social ties within and among CoPs realize our proposed (virtual) career development social structure, that unite like-minded learners with common career prospects and expert mentors. While many methods were suggested to defect or construct CoPs, in our work we build the CoPs with consideration to the personal specific preferences and predispositions of learners that don't disappear as they join CoPs and which are proven to impact their living in the CoPs, and so, they contribute to the growth and sustainability of their CoPs. We utilize Learning Analytics (LA) technique throughout the evolution of this social structure to match common learners and reinforce social ties that support joint-career vision and practices. With the emergence of data-intensive universities, the power of LA is unleashed to bring further awareness about career dispositions while producing and consuming learning.

49.2 CoPs for Career-Oriented Development

Our solution aims at augmenting the physical classroom environment which focuses on formal curriculum instruction with a virtual "cognitive apprenticeship" environment synthesized by our CoP model. This social structure influences twenty-first century education bridging the industry gap by guiding groups of learners toward a desired career path. Ancient apprenticeship methods helped earlier learners seeing parents or mentors plant or harvest corps with other partners, and piece together garments under the supervision of a more experienced tailor. We augment formal schooling with the process of becoming a member of a sustained CoP that would eventually lead to successful career, immediately upon graduation. This process involves developing an identity as a member of the community; and becoming knowledgeably skillful by moving from peripheral to full participation, progressively. The process starts by joining the most suitable CoP where members share knowledge, experiences, and passion for a predicted practice to build capabilities and maintaining momentum for a desired career. Subsequently, CoP provides an apprenticeship model to promote learning environments which render key aspects of discipline and industry domain-specific processes visible to learners, while still in academia. Based on a mentorship structure, CoP fills the current education gap to condition learners into a predicted career path. Thus, CoP acts as a virtual classroom where social interactions and collective intelligence contribute to the development of individual career readiness. In order to develop career readiness capacity, the framework of CoP-based instructional model consists of three major modules: (1) career readiness, (2) career prediction, and (3) career development.

The purpose of career readiness process is to measure the general professional dispositions required for a successful career in the twenty-first century. In previous work, we introduced the concept of career dispositions and proposed a portal application by feeding data streams gathered from learners throughout their higher education lifetime, into an analytics engine that reveals levels of professional competencies achievement and tells learners how to increase their career readiness [3]. In this paper, we present the work to develop the career prediction module.

49.2.1 Career Prediction

The career prediction module analyzes data from learners' profile and career disposition values in order to predict a hypothetical career practice and bring learners with similar career patterns together into a common cluster. This process leads to a social structure made up of CoPs that are identified to specifically respond to imminent industrial needs. To solve the cold-start problem of CoP construction, we use the career readiness data as a source for initializing groups (or clusters) of learners and denote each such cluster as a CoP (Fig. 49.1). In order to conduct this initial grouping process, we apply a clustering technique that brings a seed set of learners into an initial set of CoPs. The seed set consists of learners who achieved high scores in career disposition values that are above a given parameter threshold. There is typically at least one seed member in each cluster (CoP) for which his/her career profile matches the definition suggested by the career ontology that yielded the CoP. The rationale of privileging highly ranked learners in their career disposition to create dedicated CoPs is driven by the prospects to sustain CoPs. From this initial stage, we infer the use of career disposition values only to provide seed set of new CoPs (including the initial ones).

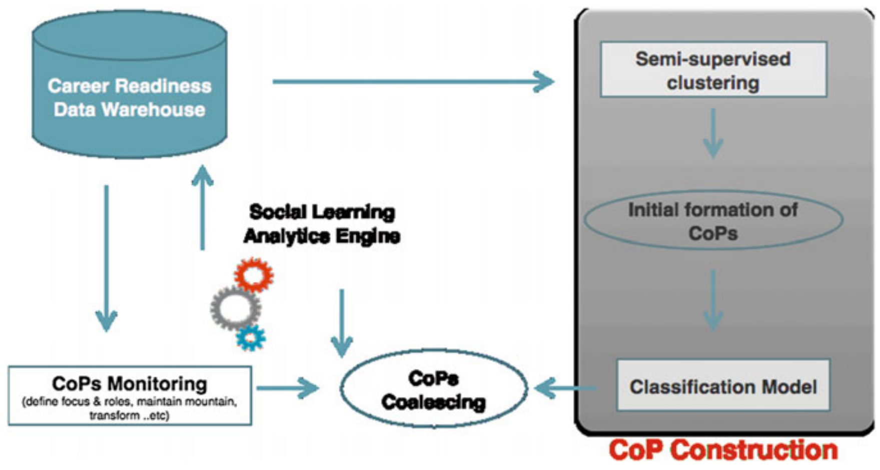


Fig. 49.1 Career prediction and CoP construction

To this end, we developed a semi-supervised clustering method to bring learners with similar professional traits that match a typical career pattern together into the same cluster. We emphasized the natural overlap nature of industrial needs and career paths by allowing each learner to be in more than one cluster. Our proposed algorithm is based on two of the most common partitioning methods: (1) Seeded K-means algorithms that use labeled examples to initialize cluster centers; and (2) Constrained K-means algorithms that enforce constraints to be satisfied during the clustering assignment; or penalize constraint violations using distance [4]. Both methods are applied using the original unsupervised K-means algorithm.

49.2.2 Fuzzy Semi-Supervised Clustering Algorithm

One challenging problem occurs when and whether a violation of the link constraint should be penalized. In traditional semi-supervised clustering algorithms, a violation of the link constraint is always penalized. Now, as we allow the instances to be associated with multiple labels, a constraint can be violated legitimately. For example, assume that instant A can be assigned to Clusters C1 and C2; and instant B is in C2 and C3. If there is a must link between A and B in C2, then using label C1 for A and C3 for B allow to violate the must-link legitimately.Thus, the penalty function needs to be redesigned to allow fuzzy labeling and to estimate if a constraint violation could be legitimate or not. In our proposed fuzzy pairwise-constraints K-means (FCKM) algorithm (see Algorithm 49.1), we first identify all the seeds S_{c1}, S_{c2},…, S_{ct} belonging to each cluster C, then we initialize the centroids of each cluster as the average of the seeds belonging to that cluster. As we allow soft constraints, namely the pairwise-constraints could be wrong, we apply a penalty function on each constraint violation. As we showed in the above example, not every violation should receive a penalty. We need to determine when a violation should not receive a penalty. Assume we are assigning the instance x_a, we develop the following new objective function, which is an updated version of previous works [4]:

$$O_{\text{new1}} = \frac{1}{2}\sum_{xcC_j} D(x_a,\mu_j)^2 + I(\text{label}((x_a,x_b)\in C_n)\neq j) \times \frac{1}{2}\sum D(x_b,\mu_j)^2 + I(\text{label}((x_a,x_b)\in C_n)\neq j)\times\frac{1}{2}\sum_{(x_a,x_b)} D(x_b,\mu_j)^2$$

Our formal algorithm is formally depicted below.

Algorithm 49.1 Fuzzy pairwise-constraints K-means (FCKM)

Input: A data set $X = \{x_a \ldots x_n\}$ to cluster, C: the number of clusters,

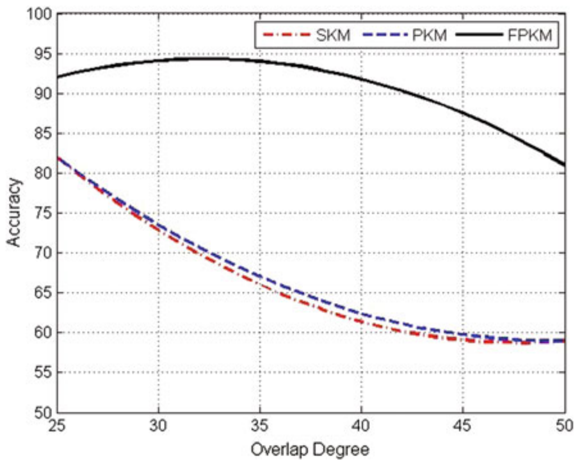
S: set of seeds, set of $C = \{(x_a, x_b)\}$, set of $C_x\{(x_a, x_b)\}$

Output: A partition of X into C clusters that is a local optima of the new objective function.

Method:

1. Initialize clusters: $\mu_c \sum_{i=1}^{t} \frac{S_{c_i}}{t}$
2. Repeat until convergence:
   (a) Assign each data point x_a to the nearest cluster $h^* = \text{argmin}_n O_{\text{new}}$
   (b) Update centroids $\mu_1 \ldots \mu_c$, according to CVQE: CentroidUpdateRule
3. Return Cclusters.

Fig. 49.2 Accuracy of our method (FPKM) in comparison with baseline schemes



49.2.3 Performance Evaluation

Using artificial data set as a first stage, we experimentally show the improved performance in terms of clustering accuracy of our proposed clustering approach when the overlap degree increases, in comparison with baseline methods of seeded (SKM) and pairwise-constraints K-means (PKM) algorithms (see Fig. 49.2). This is because the recall of FPKM is generally very high, much higher than those of the baseline algorithms, as the baseline algorithms do not consider overlaps, and thus, the assignment for the nodes in the overlapped region is relatively random.

Many true positives are missed. The recall of the fuzzy algorithm is, however, affected by the degree of overlap: The more the clusters overlap, the lower the recall is. This is obvious because with more overlap, there are more true positives we need to capture and the more true positives the algorithm tends to miss. Thus, the recall decreases, and so the overall accuracy.

49.3 Conclusion

We devised a semi-supervised clustering method to bring learners with similar professional traits that match a typical career pattern together into the same cluster. Our method aims to initially form a CoP with a seed set of learners who can drive the CoP activities and sustain its effectiveness. We emphasized the natural overlap nature of industrial needs and career paths by allowing each leaner to be in more than one cluster. Our method demonstrated higher accuracy when overlap degree increases, than the baseline methods of semi-supervised clustering methods. Hence, our method has the potential to serve as an LA tool to reveal hidden patterns of common traits among learners viewed as future candidates of the job market.

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Chapter 50
The Open Courses Project at the Eastern Macedonia and Thrace Institute of Technology

Chris Lytridis, Ioannis Kazanidis and Avgoustos Tsinakos

Abstract In this short chapter, the Open Academic Courses project at the Eastern Macedonia and Thrace Institute of Technology is discussed. The various aspects of the project both in terms of equipment as well as human resources are described. The current state of the project is also presented. Finally, the various issues and challenges met during the project are discussed.

Keywords Open courses · Distance learning · Lifelong learning

50.1 Introduction

Education is an essential tool for individuals and society to solve the challenges of the present and seize the opportunities of the future. However, the current provision of education is limited by educational institutions' capacity; consequently, this resource is available to the few and not the many [1]. Without the possibility of such wide access, knowledge cannot be dissipated, evaluated, and renewed due to geographical or financial constraints. The digital revolution offers a potential solution to these limitations, giving a global audience access to free, open, and high-quality educational resources [1]. Open access may be defined as the practice of providing online access to scientific information that is free for the end user and reusable. The benefits of open access to educational material are numerous. Students can find additional educational material to help them enhance their knowledge on specific domains. Teachers can reuse high-quality open educational material in order to upgrade existing training materials that are already providing to

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the students. Researchers can share data and develop new networks. Open educational resources include full courses, course materials, modules, textbooks, streaming videos, tests, software, and any other tools, materials, or techniques used to support access to knowledge [2].

Higher education institutions have been using the Internet and other digital technologies to develop and distribute teaching and learning for many years [3, 4]. In 2010, Massive Open Online Courses (MOOCs) were introduced as a new educational online tool which would be interactive, dynamic, and social. MOOCs differentiate from other traditional e-learning educational models because of their availability on a massive scale [5]. They focus on scalability and are designed for thousands of users, use performance rating systems and encourage interaction between students [6]. MOOC providers are mainly companies, such as Coursera, Udacity, or Miríada X, and they tend to use copyright: Unless indicated as being in the public domain or under Creative Commons licenses, the content of the site is protected by Copyright laws [7].

In Greece, every year at about 500 departments of universities taught nearly 30,000 courses. Educational materials resulting from this activity include notes, presentations, a huge number of hours of lectures, educational software, online exercises. Nevertheless, the main volume of this educational material is not widely available and easily accessible at the moment and remains limited into each academic audience. The need for the promotion and distribution of such material led to the national action "Hellenic Academic Open Courses". The Open Courses action receives a total funding of €20,000,000.

This action includes the development and creation of digital online courses, the live broadcast, recording, processing, and disclosure of lectures online. The relevant digital educational materials used in the digital lessons come from:

1. The conversion in digital form of exercises, notes, slides, and other equipment used in the educational process, or the assembly of existing electronic materials
2. The development of new educational material compatible with the deliverable services
3. The qualitative and quantitative improvement of existing digital courses.

The digital educational material will be uploaded on a relevant platform per institution and will be available with Creative Commons licenses, through a national central search portal (http://www.opencourses.gr/), where the general public will be able to browse the available courses or search for a particular subject area.

50.2 The Open Courses Project

The Eastern Macedonia and Thrace Technological Institution participates to the Open Academic Courses project by contributing a large number of subjects taught at the various departments of the institution. The developed courses are distinguished into three categories (A−, A, A+).

- A− Courses: This category provides a description, objectives, keywords, notes and presentation slides, literature and other educational materials, organized into topics.
- A Courses: They contain materials found in A− Courses and additionally include podcasts, synchronized with presentation slides.
- A+ Courses: They provide what has already been reported in previous course categories, and in addition, they include video lectures.

As all courses (regardless of their category) contain learning material in electronic form, the first step is to acquire this material and upload it to the institutional distance learning platform. The platform that was selected for this purpose at the Eastern Macedonia and Thrace Technological Institute is Moodle. The procedure for educational material acquisition is as follows: The institutional open courses administration office contacts the heads of the various departments and requests that the respective lecturers are informed and provide their teaching material in electronic form, including a form that describes their courses and includes keywords, lecture descriptions and learning objectives. The electronic material can be lecture notes, presentations, exercises, or any other material that the lectures wish to be included. As soon as the material for a particular course is received, a corresponding distance learning course is created in Moodle, and the learning material is organized in sections according to the lecturer's requirements.

As mentioned earlier, in addition to educational material in electronic form, A+ category also includes the videos of lectures. For this reason, the necessary equipment was acquired in order to record lectures and store them in high-quality digital form. Recordings of lectures can take place either during the actual lecture delivery to students with the use of portable equipment, or at a time of the lecturer's choice, using a room equipped with a static camera. Table 50.1 summarizes the recording equipment used for the realization of courses designated as A+.

As soon as a lecture is completed, the resulting video is stored on an FTP server, where it can be accessed at a later time for video editing. When the video lectures are prepared (i.e., processed, edited, and converted to an appropriate format), they have to be uploaded to the OpenDelos platform.

50.2.1 The OpenDelos Platform

OpenDelos platform has been developed by the Greek Universities network—a non-profit civil company whose members are all the Greek Higher Education and

Table 50.1 Equipment used for lecture video recordings

Camera	Quantity	Type
SONY HXR-NX30E	3	Portable
AXIS P1347—IP camera	1	Static

Academic Institutions. The purpose of the open source OpenDelos platform is the management, archiving and online broadcasting of video lectures. When a video resource is uploaded to OpenDelos, it is accompanied by metadata such as lecture title and description, lecturer's name, course name, and academic institution. The metadata are used for searches by users in the OpenDelos institutional portal (http://delos.teiemt.gr/opendelos/). Additional capabilities of the OpenDelos platform include basic video editing and presentation slide synchronization.

Even though the actual video lecture files are stored in OpenDelos, they are accessed through Moodle. Each section inside a Moodle course contains the relevant files, as well as the link to the OpenDelos environment which contains the relevant video resource. Linking is set up in such a manner, so that the OpenDelos resource is displayed without leaving the Moodle environment. An example screenshot of video lecture playback in OpenDelos is illustrated in Fig. 50.1.

Figure 50.2 illustrates the structure of an A+ course and where its various components are stored.

In this way, video lectures can be incorporated into an existing Moodle course, thus improving the educational capabilities of the original Moodle course. The same embedding/linking procedure with the OpenDelos environment would apply to other distance education platforms.

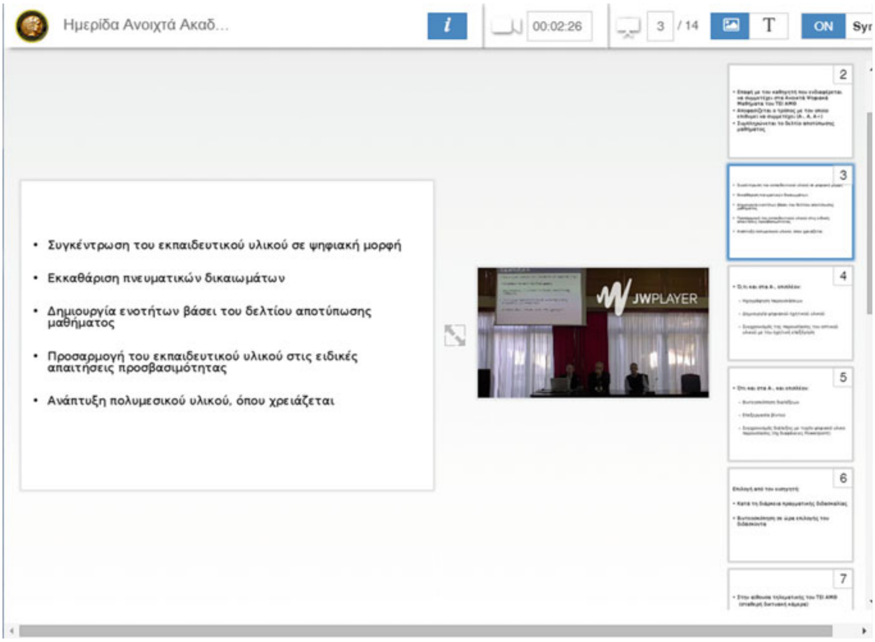

Fig. 50.1 OpenDelos video-on-demand

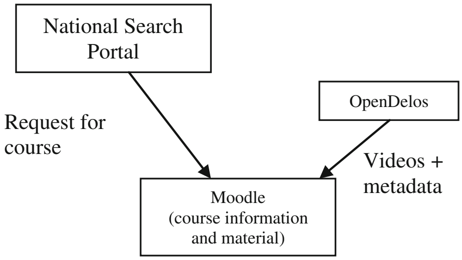

Fig. 50.2 A+ course architecture

50.2.2 Social and Personalization Tools in Open Courses

The Moodle platform contains activities and resources. Resources contain static content while activities let users interact and actively participate into the course. Moodle supports "social constructionism" and "connected knowing" perspectives using learning communities [8–10]. In order to implement this, Moodle offers 20 different types of activities available such as forums, glossaries, wikis, assignments, quizzes, choices (polls), and databases. The main power of this activity-based model comes from combining the activities into sequences and groups, which can help the instructor guide participants through learning paths.

While courses are open to visitors, Moodle activities (namely forums and chatrooms) require the user registration in order to actively participate in them. Visitors can access activity content, but they cannot interact with courses students. For this reason, student accounts were created in order to allow interaction between Open Courses Moodle users.

To this end, we are examining the idea to upgrade some of the courses into MOOCs and add more activities which require tutor participation. In this case, Moodle activities such as quiz, wiki, choice, and assignments. could be added and the tutor can mentor some groups of students for a specific time period, while students would become members of a robust virtual community.

50.3 Current State

At the moment, the project is at a stage where the educational material is being finalized and uploaded to the institutional Moodle platform and is prepared for use at the national search portal. The interconnection of the institutional platform with the national search portal is at place, and several courses of our Institute are already accessible through the portal. More courses are added constantly as material is acquired and uploaded to Moodle.

At the same time, video recording of lectures is still ongoing for the remaining semester lectures. The resulting videos are edited and gradually uploaded to the OpenDelos platform for integration with the existing Moodle courses.

It is estimated that all A− courses will have been uploaded to the Moodle platform by the end of the current semester. By the same time, the target is to prepare and make available all the A+ courses taught during the previous semester. The rest of the courses will be made available by September 2015.

50.4 Conclusions

In this article, the Open Courses action and its current state at the Eastern Macedonia and Thrace Institute of Technology were presented. Our institution contributes 36 A+ courses and more than 62 A− courses from all departments. All these courses will be available to both students and the general public. Since educators knew that their courses will be available to all the people, they updated the courses material making improvements both in quality and quantity of the course contents. Feedback by the public and educational community will motivate educators to further improve their courses.

Open education brings new opportunities for innovation in higher education that will allow institutions and academics to explore new online learning models and innovative practices in teaching and learning. To this end, in the future, some of the courses with the highest quality of Open Courses action could be transformed into MOOCs in order our institution to provide even more integrated educational services. This will open the knowledge to even more people who additionally need a certificate for their performance in these courses and now can only look for identical courses in non-native languages.

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Chapter 51
Discovering Interesting Patterns in an e-Learning System

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Abstract This paper presents a method for discovering interesting patterns in an e-learning system using a clustering method based on variable precision rough set theory and association rules. The information from each cluster is then used to generate interesting rules in order to help teachers in the learning process and to understand students' behavior. To accomplish this, a database with students enrolled for a "Database" course is analyzed and the presented method discovers rules of the students' behavior regarding the assignments, course quizzes, and also the rules of student's interaction with teacher and other students.

Keywords e-learning · Variable precision rough set · Clustering · Rules

51.1 Introduction

The analysis of students' performance and behavior is one of the most important and useful applications of educational data mining and its goal is to discover patterns for student course behavior and activity [8].

In this study, two of the most important data mining techniques are used in order to offer methods for understanding, processing, and modeling data in an e-learning system: variable precision rough set (VPRS) and association rule techniques.

Many studies have shown that the use of rough set theory helps formulate clearer decision-making projects and enhance the effectiveness of the research while doing optimization [13]. The research related to education of Qu and Wang [14] provided a basis of personalized teaching strategies in distance learning Web site by the analysis of reduct and attribute significance. In [9], the study analyzed students'

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misconception based on rough set theory. In [12], the variable precision rough set is used to cluster the student suffering from study's anxiety. Although the rough set theory is rarely used in education, in this study, we use its characteristics, which are very suitable for discovering rules useful in educational process.

On the other hand, association rule mining (ARM) is one of the most popular data mining techniques successfully applied in e-learning. Its objective is to discover patterns in datasets. An excellent review about the application fields of ARM in educational problems was made in [7].

VPRS model is an extension of the classical rough set theory (RST) as a tool for classification of objects. VPRS deals with partial classification by introducing a probability value β. The β represents a bound on the conditional probability of a proportion of objects in a condition class which are classified into the same decision class [3]. Ziarko [15] considered β as a classification error, defined to be in the interval [0; 0.5), and his model degenerates into the classical rough set model if $\beta = 0$. Some researchers have studied VPRS models and got some meaningful results [1, 3, 5].

The purpose of this paper is to combine the VPRS model for students' clustering with association rule generation. By calculating the β-reducts and the mean variable precision roughness of attributes, the clustering attribute is determined [12]. Then, the decision rules capable to observe students' activity are obtained from each cluster. All the process is automatically done. The determination of the clustering attribute is an important step, because it plays also the role of decision attribute in the process of association rule generation.

We firstly present how we model the information about students' activity in the e-learning system in Sect. 51.2. In Sect. 51.3, basic notions of RST and VPRS models are introduced to facilitate the understanding; also, we present the methods of clustering and rule generation. An illustrative example is analyzed in Sect. 51.4 to show the feasibility of the proposed approach. The results of experiments are summarized in Sect. 51.5.

51.2 Student Representation and Discretization

We have collected data from online course activity provided by Moodle [2] that is one of the most widely used open source learning management system. In fact, we have used the following data based on student "Database" course activity [8, 11]: Nassignment—number of assignments taken; Nquiz—number of quizzes taken; Nquiz_p—number of quizzes passed; Nquiz_f—number of quizzes failed; Nmessages—number of messages sent to the chat; Nmessages_ap—number of messages sent to the teacher; Nposts—number of messages sent to the forum; Nread—number of forum messages read; Total_time_assignment—total time spent on assignment; Total_time_quiz—total time used in quizzes; Total_time_forum—total time used in the forum; Mark—final mark the student obtained in the course.

Since the data provided by Moodle are structured, we did not necessitate any other preparation of data [8]. So, we directly discretize them, transforming numerical values into categorical ones for a good interpretation and understanding. We have used the manual method for discretizing all attributes, so the teacher has to specify the cutoff points. The mark descriptor has four values: insufficient, if value <5; average, if value >5 and <7; good, if value >7 and <9; and excellent, if value >9. The other attributes have the values: low, medium, and high [8, 11].

A student is represented in Prolog by means of a term:

```
student(ListofDescriptors)
```

where the argument is a list of terms used to specify the student attributes.

The term used to specify the student attributes is of the form:

```
descriptor(DescriptorName, DescriptorValue)
```

51.3 Modeling of Student Information Using Rough Sets

51.3.1 Rough Sets

Rough set theory is an intelligent mathematical tool and it is based on the concept of approximation space [6]. In rough set theory, the notion of information system determines the knowledge representation system.

In this section, we recall some basic definitions from the literature [6].

Let U denote a finite non-empty set of objects (students) called the universe. Further, let A denote a finite non-empty set of attributes. For every attribute $a \in A$, there is a function a: $U \rightarrow$ Va, where Va is the set of all possible values of a, to be called the domain of a. A pair IS = (U, A) is an information system. Usually, the specification of an information system can be presented in the tabular form. Each subset of attributes $B \subseteq A$ determines a binary *B-indiscernibility* relation IND(B) consisting of pairs of objects indiscernible with respect to attributes from B like in (51.1):

$$\mathrm{IND}(B) = \{(x, y) \in U \times U : \forall a \in B,\ a(x) = a(y)\} \tag{51.1}$$

IND(B) is an equivalence relation and determines a partition of U, which is denoted by U/IND(B). The set of objects indiscernible with an object $x \in U$ with respect to the attribute set, B, is denoted by $I_B(x)$ and is called *B-indiscernibility* class:

$$I_B(x) = \{y \in U : (x, y) \in \mathrm{IND}(B)\} \tag{51.2}$$

$$U/\mathrm{IND}(B) = \{I_B(x) : x \in U\} \tag{51.3}$$

It is said that a pair $AS_B = (U, \mathrm{IND}(B))$ is an approximation space for the information system IS = (U, A), where $B \subseteq A$.

The *B-lower approximation* $X, \underline{B}X$ is the union of all equivalence classes in IND (B) which are contained by the target set X. The lower approximation of X is called the positive region of X and is noted as POS(X).

$$\underline{B}X = \cup\{w_i|w_i \subseteq X\} \tag{51.4}$$

The *B-upper approximation* $\overline{B}X$ is the union of all equivalence classes in IND(B) which have non-empty intersection with the target set X.

$$\overline{B}X = \cup\{w_i|w_i \cap X \neq \emptyset\} \tag{51.5}$$

The accuracy of a rough set is defined as follows:

$$\alpha_B = \mathrm{cardinality}(\underline{B}X)/\mathrm{cardinality}(\overline{B}X) \tag{51.6}$$

If the accuracy is equal to 1, then the approximation is perfect.

51.3.2 Variable Precision Rough Sets

Variable precision rough set (VPRS) extends rough set theory by the relaxation of the subset operator [15]. So, the objects are classified with an error smaller than a certain predefined level.

We recall some definitions from the literature [1, 3, 5, 15].

Let $X, Y \subseteq U$ be two non-empty subsets of the universe U. The error classification rate of X relative to Y is denoted by $e(X, Y)$ and is defined by:

$$e(X,Y) = \begin{cases} 1 - \frac{|X \cap Y|}{|X|}, & |X| > 0 \\ 0, & |X| = 0 \end{cases} \tag{51.7}$$

Let β be a real number within the range, $0 \leq \beta < 0.5$, X be a subset of the universe U, and B be an attribute subset of A. Then, the β-lower and β-upper approximations are as follows:

$$\underline{B}_\beta X = \{x \in U/e(x,X) \leq \beta\} \tag{51.8}$$

$$\overline{B}_\beta X = \{x \in U/e(x,X) > 1 - \beta\} \tag{51.9}$$

The accuracy of approximation variable precision (accuracy of variable precision roughness) of any subset $X \subseteq U$ with respect to $B \subseteq A$ is as follows:

$$\alpha_{B_\beta} = \frac{|\underline{B}_\beta X|}{|\overline{B}_\beta X|} \tag{51.10}$$

In [12], it is proved that the accuracy of approximation using variable precision of attributes is more accurate for selecting clustering attribute.

Let the attribute be $a_i \in A$, with $V(a_i)$, k-different values, say c_k, $k = 1, 2, \ldots, n$. Let $X(a_i = c_k)$, $k = 1, 2,\ldots, n$, be a subset of the objects having k-different values of attribute a_i.

The accuracy of the set $X(a_i = c_k)$, $k = 1, 2, \ldots, n$, with respect to a_j, where $i \neq j$, is defined as follows:

$$\alpha_{\beta a_j}(X|a_i = c_k) = \frac{|\underline{B}_\beta X_{a_j}(a_i = c_k)|}{|\overline{B}_\beta X_{a_j}(a_i = c_k)|} \tag{51.11}$$

The mean accuracy of attribute $a_i \in A$ with respect to $a_j \in A$, where $i \neq j$, denoted by $\mathrm{MAC}_{a_j}(a_i)$, is defined as in [12]:

$$\mathrm{MAC}_{a_j}(a_i) = \frac{\sum_{k=1}^{n} \alpha_{\beta a_j}(X|a_i = c_k)}{n} \tag{51.12}$$

where n is the number of values for attribute a_i.

For n attributes, mean variable precision roughness of attribute $a_j \in A$ is denoted as $\mathrm{MA}(a_j)$ and is computed as follows:

$$\mathrm{MA}(a_j) = \mathrm{avg}\left(\mathrm{MAC}_{a_j}(a_i)\right), \quad i \neq j, i = 1, \ldots, n \tag{51.13}$$

51.3.3 Clustering and Decision Rule Extraction in the e-Learning System

The algorithm for students' clustering is based on variable precision rough sets by computing the mean accuracy of attributes in order to select the attribute used to group students in clusters. We will select a clustering attribute among all candidates, and there is no predefined clustering attribute [12]. To obtain the values of VPRS, firstly, we must obtain the equivalence classes induced by indiscernibility relation of singleton attribute.

The steps of the algorithm for clustering and extraction of decision rules are as follows:

- Determine the equivalence classes of objects using the indiscernibility relation.
- Compute the error classification of each attribute with respect to all other attributes.
- Determine the set of all β-reducts of each attribute.
- Compute the mean accuracy of each attribute with respect to all other attributes.
- Select the attribute with the maximum mean accuracy to use it as clustering attribute.
- Determine the clusters, and for each cluster, determine the frequent itemsets using Apriori algorithm [10].
- The generated rules have the body composed by categorical values, and the head is represented by the clustering attribute.

A rule is represented using a Prolog fact:

```
rule(ClusteringDescriptor, Accuracy, Coverage,
          ListofStudentDescriptors)
```

where *Accuracy* is the rule accuracy computed as in (51.14), *Coverage* is the rule coverage computed as in (51.15), the body of the rule is composed by conjunctions of student descriptors, while *ClusteringDescriptor*, the head of the rule, is the clustering attribute.

For a rule *if descriptors then clustering descriptor*, we may define the accuracy (a) by:

$$a(rule) = \frac{cardinality(descriptorSet \cap clusterSet)}{cardinality(descriptorSet)} \tag{51.14}$$

where the set $descriptorSet \cap clusterSet$ is composed of student descriptors which have a certain *descriptorSet* and a *clustering descriptor*.

The coverage(c) of a rule is defined by:

$$c(rule) = \frac{cardinality(descriptorSet \cap clusterSet)}{cardinality(clusterSet)} \tag{51.15}$$

51.4 Case Study for an e-Learning System

The experiments presented in this paper are realized in the e-learning system containing 40 students enrolled for *Database* course.

We analyze the students' behavior from the point of view of course assignments and also from the point of view of interaction with the other participants.

So, we have the information system (U, C), where

C = {Nassignment, Nquiz, Nquiz_p, Nquiz_f, Total_time_assignment, Total_time_quiz, Nmessages, Nmessages_ap, Nposts, Nread, Total_time_forum, Mark}

In Table 51.1, the partial e-learning system is presented. For the simplicity of presentation, we consider that *C = {Nassignment, Nmessages_ap, Nposts, Mark}.*

The steps to determine the clustering attribute are as follows:

1. The equivalence classes induced by each attribute are as follows:

X(*Nassignment* = *high*) = {R_1, R_2, R_7, R_8}
X(*Nassignment* = *low*) = {R_3, R_4}
X(*Nassignment* = *medium*) = {R_5, R_6}

X(*Nmessages_ap* = *high*) = {R_3, R_8}
X(*Nmessages_ap* = *medium*) = {R_2, R_5}
X(*Nmessages_ap* = *low*) = {R_1, R_4, R_6, R_7}

X(*Nposts* = *high*) = {R_7, R_8}
X(*Nposts* = *medium*) = {R_2, R_3, R_4, R_5}
X(*Nposts* = *low*) = {R_1, R_6}

X(*Mark* = *excellent*) = {R_2, R_8}
X(*Mark* = *average*) = {R_1, R_3, R_5, R_6}
X(*Mark* = *insufficient*) = {R_4}
X(*Mark* = *good*) = {R_7}

2. Determination of error classification for each attribute.

The error classification of attribute *Nposts* with respect to Mark is:
e(average, *Nposts* = *high*) = 1 − 0/4 = 1
e(average, *Nposts* = *medium*) = 1 − 2/4 = 1/2
e(average, *Nposts* = *low*) = 1 − 2/4 = 1/2

e(excellent, *Nposts* = *high*) = 1 − 1/2 = 1/2
e(excellent, *Nposts* = *medium*) = 1 − 1/2 = 1/2
e(excellent, *Nposts* = *low*) = 1 − 0/2 = 1

e(good, *Nposts* = *high*) = 1 − 1/1 = 0
e(good, *Nposts* = *medium*) = 1 − 0/1 = 1
e(good, *Nposts* = *low*) = 1 − 0/1 = 1

Table 51.1 Partial student information system

U	Nassignment	Nmessages_ap	Nposts	Mark
R_1	High	Low	Low	Average
R_2	High	Medium	Medium	Excellent
R_3	Low	High	Medium	Average
R_4	Low	Low	Medium	Insufficient
R_5	Medium	Medium	Medium	Good
R_6	Medium	Low	Low	Average
R_7	High	Low	High	Good
R_8	High	High	High	Excellent

Table 51.2 Mean accuracy computation

Attribute (with respect to)	Mean accuracy			Mean variable precision roughness
Nassignment	Nposts 0.16	Nmessages_ap 0	Mark 0.12	0.09
Nposts	Nassignment 0.16	Nmessages_ap 0.16	Mark 0.33	0.21
Nmessages_ap	Nassignment 0	Nposts 0.16	Mark 0	0.05
Mark	Nassignment 0.024	Nmessages_ap 0.33	Nposts 0.38	0.24

e(insufficient, $Nposts$ = $high$) = 1 − 0/1 = 1
e(insufficient, $Nposts$ = $medium$) = 1 − 1/1 = 0
e(insufficient, $Nposts$ = low) = 1 − 0/1 = 1

3. Determination of β-reducts and mean accuracy of attributes:

$$\underline{B}_\beta(Nposts = high) = \{\mathrm{R}_7\}; \underline{B}_\beta(Nposts = medium) = \{\mathrm{R}_4\};$$
$$\underline{B}_\beta(Nposts = low) = \{\phi\};$$
$$\overline{B}_\beta(Nposts = high) = \{\mathrm{R}_1, \mathrm{R}_3, \mathrm{R}_4, \mathrm{R}_5, \mathrm{R}_6, \mathrm{R}_7\}; \overline{B}_\beta(Nposts = medium) = \{\mathrm{R}_7\}$$
$$\overline{B}_\beta(Nposts = low) = \{\mathrm{R}_2, \mathrm{R}_4, \mathrm{R}_7, \mathrm{R}_8\}$$
$$\alpha_{\beta Mark}(X|Nposts = high) = \frac{1}{6}; \alpha_{\beta Mark}(X|Nposts = medium) = \frac{1}{1};$$
$$\alpha_{\beta Mark}(X|Nposts = low) = 0.$$
$$MAC_{Mark}(Nposts) = \frac{\frac{1}{6} + 1 + 0}{3} = 0.38$$

Following the same procedure as described above, the mean accuracy of attributes with respect to each other is computed. These calculations are summarized in Table 51.2.

From Table 51.2, the highest of mean accuracy of attributes is attribute Mark. Thus, the attribute Mark is selected as a clustering attribute. To generate rules, the Apriori algorithm is used to generate frequent itemsets [10].

51.5 Experiments and Conclusion

The analyzed database contains information about 40 students, each described by 12 descriptors: *Nassignment, Nquiz, Nquiz_p, Nquiz_f, Total_time_assignment, Total_time_quiz, Nmessages, Nmessages_ap, Nposts, Nread, Total_time_forum, and Mark*.

The selected attribute for clustering is *Mark* with variable precision roughness 0.03. Based on mark values, four clusters are generated, as presented in Table 51.3.

Some examples of rules generated from each cluster are presented below.

Table 51.3 Generated clusters with attribute *Mark* as clustering attribute

Clustering attribute (Mark)	No. of students
Good	15
Average	10
Excellent	7
Insufficient	8

The following rule shows that students who completed a high number of assignments and quizzes obtained an excellent score. This means that these activities are very important during the course examination.

```
Rule(excellent,3/3,3/7
[descriptor(Nassignment, high),descriptor(Nquiz, high]).
```

The rule generated for *good* mark indicates that even if the student recorded a good score for assignment and quizzes, the final mark was influenced by the little interaction with the teachers and other students.

```
Rule(good, 6/8,6/9,
[descriptor(Nassignment, high),descriptor(Nquiz, high),
descriptor(Nposts, low),descriptor(Nmessages, low)]).
```

The next rule shows also the importance of the activities like assignment and quizzes. The mark also is influenced by the number of posts and the time spent on the forum. In the future, the teacher could pay more attention to the students with short time spent on the forum.

```
Rule(average, 5/7,5/10,
[descriptor(Nassignment, medium),descriptor(Nquiz, medium),
descriptor(Nposts, low),descriptor(Total_time_forum, low)]).
```

The following rule shows that the students with a low number of passed quizzes and a low number of messages and posts are failed. Using this information, the teacher could pay more attention to these students because they have a higher probability of failing.

```
Rule(insufficient, 3/4,6/8,
[descriptor(Nquiz_p, low),descriptor(Nmessages, low),
descriptor(Nposts, low)]).
```

It can be observed that the proposed methods could assist the teacher in the e-learning system; thus, by analyzing the generated rules, the teacher could take pedagogical decisions regarding the presentation of course or the interaction with students. Also, he could make recommendations to students during a course study. The rules could also be used to classify students before the final examination and predict their mark.

In the future work, it would be interesting to experiment the efficiency of the proposed methods and to analyze the results for more courses in order to discover the students' behavior. It would be also very useful to do experiments using more experts in order to analyze the obtained rules for discovering interesting relationships. Also, in the future, we intend to use the generated rules to classify students.

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Chapter 52
Involving Learners in Content Analysis to Empower A Community of Inquiry

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Abstract This paper investigates how learners can be involved in the content analysis during asynchronous discussion and the benefits of this process for building a community of inquiry (CoI). Specifically, nine learners and two instructors of an MSc course on distance learning participated in an asynchronous discussion in order to collaboratively solve a design problem. Through the discussion, learners were asked to classify their own, their peers' and instructors' messages based on particular coding schemes that reflect the cognitive and teaching presences of the CoI framework. In this way, learners' classification data were captured and analyzed in order to evaluate the way they classify messages compared to experts' coding. Specific patterns were revealed providing evidence about the ability of learners in accurately acknowledging the majority of the messages but also cases in which learners agree in an alternative coding than the experts' one, opening up a new perspective on coding, the learners' perspective. The development of metacognitive skills was also evaluated based on questionnaires that students completed reflecting on this experience.

Keywords Content analysis · Community of inquiry · Blended learning · Asynchronous forum

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52.1 Introduction

According to [1], blended learning is "the organic integration of thoughtfully selected and complementary face-to-face and online approaches." This is consistent with the view that it is important to explore new forms of interaction analysis in blended learning environments to explicate the complexity of the teaching and learning transaction that takes place in such environments [2–4]. To this end, the community of inquiry (CoI) framework has been greatly used for content analysis to measure the development of the teaching, social and cognitive presences through asynchronous discussions in a blended learning context [5]. Its coding schemes developed to support analysis of all the presences are widely employed [6–8].

However, a practical issue is that content analysis is usually performed manually which is a time-consuming process employing two or more researchers for message analysis, test agreement, negotiation and review. Moreover, the large amount of data, due to the number of forum messages, hinders the coding process further. So, although the coding information provides great opportunities to comprehend and extend the knowledge presented in situations where there is a high number of students [9], transcript analysis cannot be used at real time for the revaluation of community development and redesign of the course during the learning process. Another issue is that most experimental results cannot be generalized because of the number of the CoI members in the relevant researches or because of the context or other factors that may have affected the results. As a consequence, the research findings fail to generalize reliable data about the effectiveness of instructors' interventions in supporting the development of a COI educational experience [10]. Thus, a challenging issue in this context is to involve content analysis procedures during the discussion and use these data in order to support learners or empower teachers' involvement enabling the community development.

In order to address these problems, the research community discusses at a very early stage, the development of relevant tools to automate the content analysis process focusing on the latent and/or manifest elements of communication [11–13]. Currently, there are several proposals in progress for automating the content analysis process lacking still to present satisfactory and reliable results in a real context. One of the main reasons is the latent content of communication which is difficult to reliably classify, because human coders use their own schemas to project meaning onto the text and to interpret text through their own personal perspective.

In this line of research, we attempt to contribute to the facilitation of discussion in real time by shifting the coding procedure to learners during a critical inquiry discussion. In this way, each student's perspective of the community development could open to learners in real time, stimulating reflection and metacognitive processes and probably enabling the teacher to facilitate discourse for optimal achievement of critical thinking. Actually, for learners to become metacognitively aware, it is important to understand the inquiry process, because awareness of inquiry phases can be extremely useful in selecting specific learning strategies [14].

Our approach focuses on the learner, not only as a recipient of information but also as an active member of the transcript analysis process. Accordingly, Pawan et al. [15, 16] have proposed a similar procedure of self-coding as a learning activity. In these procedures, it is suggested that self-coding, as a metacognitive strategy, is based on the theory that self-awareness of the purpose and outcomes of collaborative interaction has educational value [17]. Based on this approach, we further propose the process of self, peer and instructors' message content analysis as a promising way to achieve metacognition. This study is the first step toward the development of a visualization content analysis tool that will reflect student development based on CoI as well as the impact of teacher involvement helping them intervene accordingly.

52.2 Peer Content Analysis in INSPIRE*us*

The asynchronous discussion took place in the online forum of the educational adaptive hypermedia system INSPIRE*us* [18]. Discussion forums in INSPIRE*us* have been extended with a classification functionality allowing its users to classify their own and other participants' messages. Thus, through the discussion, the participants are able to classify their own and their peers' messages by selecting the appropriate category (see Fig. 52.1, *selection icon for each category*) from a multiple-choice menu containing four options (see Fig. 52.1, *selection icon for the pop-up window*). Each option corresponds to a specific category of cognitive presence [14] (see Fig. 52.1, *pop-up window with the four cognitive presence categories*) as these are presented in Table 52.1, row cognitive presence. In the

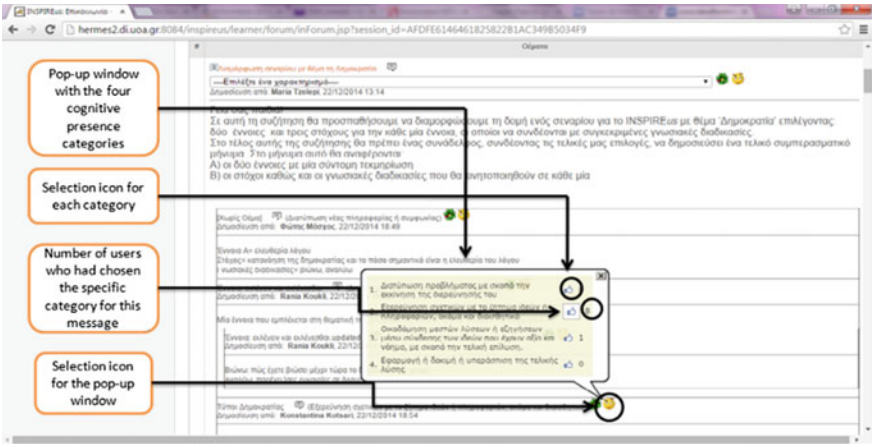

Fig. 52.1 A screenshot of the forum of INSPIRE*us* presenting the coding functionality

Table 52.1 CoI categories and their indicators in an asynchronous discussion [14]

	Categories	Indicators (examples only)
Cognitive presence	Triggering event	Sense of puzzlement
	Exploration	Information exchange
	Integration	Connecting ideas
	Resolution	Application
Teaching presence	Design and organization	Setting curriculum and activities
	Facilitating discourse	Shaping constructive exchange
	Direct instruction	Focusing and resolving issues

same way, students are allowed to code instructors' posts according to the three teaching presence categories as these are presented in Table 52.1 [7].

Moreover, students can also choose "like" for an instructor's post. For both cognitive and teaching coding schemes, they can select only one category for each post and they are free to change their classifications during the discussion. They are also able to see how many users (students and instructors) have chosen each category for every message (see in Fig. 52.1, *number of users who had chosen the specific category for this message*). All the students' choices are recorded by the system.

52.3 Empirical Study

In this section, we describe the research design, the data collection process, the instruments used, the analysis process adopted and the results of the study performed with 9 MSc students of the University of Athens attending a postgraduate course on digital technologies in distance learning. Through the discussion, students were involved in self, peers' and instructors' message assessment through particular coding schemes and instructors' message preference ("Like" selection).

In particular, before the discussion activity, two of the researchers presented the CoI framework and discussed with the students the scope of the three presences: cognitive, social, and teaching. The discussion topic was about the design of an educational scenario for the adaptive educational system INSPIRE*us* and particularly about the selection of the main concepts underlying a specific scenario proposed by the researchers. This was a preparatory activity aiming to familiarize students with the instructional design of INSPIRE*us*. During the discussion, they were able to code their own (cognitive presence categories), peers' (cognitive presence categories) and instructors' (teaching presence categories) messages. They also completed an evaluation questionnaire (see Appendix).

In this study, the following questions are investigated: (1) How students code messages based on a cognitive/teaching presences coding scheme? (2) How did the coding procedure affect students' perception of the discussion enabling the development of metacognitive skills?

Data collection. In order to address the research questions, several types of data were gathered as part of this research: (1) log data reflecting (a) students' classifications based on the cognitive presence coding for their own and peer messages as well as (b) the number of "Likes" of instructors' messages; (2) asynchronous forum messages; and (3) evaluation questionnaire of the classification experience.

In particular, the evaluation questionnaire included 9 questions: 2 nominal scale and 7 open-ended questions prompting the participants to argue about their selections and propose new ideas (see Appendix). The questionnaire is organized as follows: (1) Part A includes 4 questions that assess students' perceptions about the development of metacognitive skills and particularly how the classification procedure affected the way they perceived the discussion and (2) part B includes 5 questions that explore the difficulties that students faced in classifying messages.

Data analysis. Aiming to answer research question 1, we followed a content analysis procedure involving experts, while for research question 2 we analyzed students' answers to the evaluation questionnaire. The content analysis procedure used the message as the unit of analysis for the asynchronous discussion as (a) it has mostly been used for CoI [7–9], (b) it is objectively identifiable [19] and (c) "it is a unit whose parameters are determined by the author of the message" [19] who, in our case, is actually the person who initially coded this message. So, even if a message may contain contradictory meanings which lead to different categories [20], the message's author is most appropriate to state which is the main purpose of the message.

The content analysis procedure has been organized in two phases:

Phase A. The messages were initially analyzed by two expert coders (one of them participated in the discussion as instructor, while the second one was an expert on COI coding) in order to have a reliable coding to assess students' classification. The analysis was based on the practical inquiry descriptors and indicators (see Table 52.1). In cases of coders' disagreement, the resolution came through discussion so as to convert to consensus. In this way, they resulted to a unique category for each message, ensuring this way the reliability of the coding.

Phase B. Then, we used Cohen's kappa coefficient in order to test whether the student approaches a reliable coding perspective without this agreement being resulted randomly (kappa takes into consideration the agreement by chance). By this way, we are able to distinguish students whose disagreement on encodings may be derived from a different perspective rather than just guess. In this process, we also explored various instances of disagreement among students and teachers but agreement among students. Lastly, we explored the instructors' messages that were positively characterized by students.

Results Two of the most popular techniques for calculating the percent agreement of content analysis are Holsti's coefficient of reliability and Cohen's kappa. We choose to measure inter-rater reliability following the coding suggestions of [3] as

Table 52.2 Coding agreement between each student's classification and experts' coding

Students	Agreement (%)	Cohen's kappa	*p*
Student 1	85	0.726	0.000
Student 2	83	0.742	0.000
Student 3	80	0.622	0.000
Student 4	80	0.688	0.000
Student 5	76	0.463	0.005
Student 6	73	0.459	0.018
Student 7	58	0.401	0.000
Student 8	40	0.333	0.005
Student 9	38	0.381	0.008

well as the research methodology proposed in [7]. The inter-rater reliability analysis using the Cohen's kappa statistic and Holsti's coefficient reliability was found to be kappa = 0.92 ($p < 0.001$) and C.R. = 0.88.

The discussion consisted of 37 posts, of which 10 were posted by instructors and 27 were posted by the students. All the students' messages belong to cognitive presence categories. The first message of the discussion was the triggering event of the discussion provided by the instructor. As far as the students' messages are concerned, we observed that 44 % of the messages were classified in the exploration category, 52 % were classified in the integration category and one message was in the resolution category.

Research Question 1. *How students code messages based on cognitive/teaching presences scheme?*

Initially, we explored at what level the student's classification agrees with the experts' coding. Coding agreement was calculated for each student's classification with the use of Cohen's kappa statistical measurements, including also percentages of agreement (see Table 52.2).

The conventional level of inter-rater reliability is not clearly declared yet [21]. For this reason, we choose a well-accepted guideline for scale indication, meaning five different levels of agreement [22]. For Cohen's kappa, [22] characterized "values < 0 as indicating no agreement, 0–0.20 as slight, 0.21–0.40 as fair, 0.41–0.60 as moderate, 0.61–0.80 as substantial and 0.81–1 as almost perfect agreement".

There are three students (Students 7, 8, and 9) whose kappa values represent fair strength of agreement. The specific students, answering question 5 from part B of the questionnaire (see Appendix), referred to the difficulty of distinguishing between the third and fourth classification. Indeed, from the database log files, above the 90 % of "ambiguous" messages belonged to one of these two categories and most of them were the messages that the three students had coded differently than the experts.

Then based on the cognitive presence coding, we explored the features of the messages of which experts' coding vary from the students' ones. According to the classification data logs:

1. The 19 of the 27 messages that were exchanged in the forum were classified from more than 65 % of the students at the same category with the one proposed by the experts.
2. In the remaining eight messages, less than 65 % of the students had categorized each message in the same category as the experts' coding.
3. Two from these 8 "low agreement" messages had been coded by the experts as "exploration" category while by the students as "triggering event" category. These were also the two first messages of the discussion in chronological order (Table 52.3). An explanation can be given based on the students' answers to question 4 of part B of the questionnaire, on the difficulties of classifying peers' messages. Most of the students, who had classified differently, messages 1 and 2, answered that at the beginning of the discussion *they were confused*.
4. From the rest six messages, five were classified in integration category in experts' coding, while most student coders have chosen resolution category. The last one message was classified in resolution category in experts' coding, while most student coders have chosen integration category. Actually three students, that responded to question 5 of part B of the questionnaire and claimed that they *found it difficult to distinguish the third from the fourth category in the messages,* had coded the specific messages differently than the experts' coding. Indeed, three of these messages had initially been coded differently by both experts. Analyzing the messages' content, we found that these messages could be either coded as belonging to integration or resolution category. So, these messages could not be reliably coded since the students could select only one category for each message.

A very interesting issue observed was that most students, who chose a different categorization from the experts' coding, mostly agreed among themselves on the category chosen. Table 52.3 shows the following: (a) the number of the discussion message according to chronological order (column M), (b) message category according to experts' coding (column MC), (c) number of students who coded the message (column NS), (d) number of students whose classification differs from the experts' coding (column NDS), (e) percentage of number of students who chose a different category from the experts' one in relation to the number of students that coded the message (column FDS), (f) message category most often chosen by students who categorized the message differently than the experts' coding (column DC), (g) number of students who chose the most often selected message category that differed from experts' coding, (column NCS) and (h) percentage of number of students who chose the most often selected message category that differed from experts' coding, in relation to the number of students that coded the message (column FCS).

For example, a closer examination of message 19 (see Table 52.3, line 5) shows that from the seven students who coded the message (see Table 52.3, line 5—column NS), all disagreed with the initial experts' coding (integration) (see Table 52.3, line 5—column NDS) but agreed with each other in a different category

Table 52.3 Students' and experts' coding for the eight messages which, over 65 % of students, coded differently than the experts did

M	MC	NS	NDS	FDS (%)	DC	NCS	FCS (%)
1	2	8	4	50	1	4	50
2	2	8	3	38	1	3	38
15	3	7	6	86	4	5	71
18	3	8	4	50	4	3	38
19	3	7	7	100	4	7	100
24	4	7	3	43	3	3	43
25	3	7	3	43	4	3	43
26	3	6	2	33	4	2	33

(resolution) (see Table 52.3, line 5—column FCS). Reading the content of this message again, we realize that this message is the first comprehensive effort in the discussion for a solution, examining all the parts of the initial problem which is the triggering event of the discussion. We can, therefore, only hypothesize that this message could reasonably be interpreted as a resolution phase by the rest of the students.

According to the *teaching presence coding,* we also explored the CoI categories chosen by the experts' coding, for the most preferable instructors' messages (those with the most "Likes"). The message with most Likes (almost 100 %) was of the "facilitating discourse" category. Students managed to appropriately characterize the message. Most of them also noted, at question 3 of part A of the questionnaire, that messages that facilitated discussion were the most useful ones.

Three students also noted at questions 1 and 2 of part B of the questionnaire that they faced difficulties while categorizing specific messages belonging to more than one category. Actually, these specific messages (instructors' messages 2 and 4) that have been reported in open question 3 of part B were characterized by the experts as belonging to two different categories of teaching presence.

Research Question 2. *How did the coding classification procedure affect students' perception of the discussion enabling the development of monitoring skills?*

Students' answers about the metacognitive benefits of coding peers' posts were positive (Appendix, question 2 of part A of the questionnaire). In this question, 56 % of the students answered "Strongly Agree" and the rest of them answered "Agree." There was not observed a certain tendency of students' perception on metacognitive benefits from coding instructors' posts (Appendix, question 1 of part A of the questionnaire). In this question, 50 % of the students answered "Agree" and 50 % of the students answered "Disagree." According to students' answers to the questions 1, 2 and 3 of part B of the questionnaire, this may be because the students have encountered difficulties with the classification of instructors' messages and three of them could not distinct teaching categories when coding.

52.4 Conclusions and Discussion

In this paper, we propose a novel content analysis approach based on the CoI framework. This approach is based on students' classifying their own, peers but also instructors' messages during an asynchronous discussion. Self, peers' and instructors' message coding process involves students into the inquiry process and provides awareness and metacognition, aspects that are central to successful inquiry [14]. This also confronts the issue of time-consuming content analysis that takes place after the completion of the discussion and therefore deprives instructor of valuable feedback.

The results of this research provide evidence about the effectiveness of the proposed content analysis procedure due to the sufficient level of coding agreement between the expert coders and the majority of the students (coders). The majority of students had Cohen's kappa values between 0.73 and 0.46 (moderate to substantial agreement). For those who were in fair agreement, it was found that they were aware of the coding difficulty by acknowledging specific characteristics of the messages they found more difficult to code and by acknowledging the classifications they had difficulty to distinguish. On the other hand, the messages for which encoding showed higher disagreement between students and the experts' coder revealed that in some cases, students agreed with each other in a different encoding than the experienced coder. This may happen because of students' different perspective or as an influence of their peers' classification choices as they had access to these data. In the future, we intend to hide this information in order to clarify this issue. In addition, messages with high frequency of low coding agreement between students' and experts' coding, revealed that the four given choices of the cognitive presence coding scheme are not enough to express all the possible categories that a message can belong to.

In any case, students consider that the content analysis process enabled them to elaborate on their own, peers' and the instructor's messages identifying interesting perspectives that they could not otherwise be aware of. Furthermore, the proposed strategy looks promising for cultivating metacognitive skills through a semiautomated content analysis method. The work presented in this paper will be continued since the limited number of students of this pilot study prevents generalization of the findings. Thus, based on the current evidence, we intent to redesign the study and conduct experiments with more students in order to further examine the impact of this classification method in the learning process as well as functionality and visualization aspects of a tool facilitating online peer content analysis.

Appendix

Questionnaire
Part A
Q.1. Did the classification of instructors' messages give a different perspective on the discussion? (closed question)
Q.2. Did the classification of peers' messages give a different perspective on the discussion? (closed question)
Q.3. When did you choose "Like" for your instructors' messages?
Q.4. Generally which function did you find useful: Classification or "Like"? Why?
Part B
Q1. What made it difficult to classify instructors' messages?
Q2. Were the descriptions of the categories of teaching presence accurate and distinct?
Q3. Which instructors' messages did you find difficult to classify?
Q4. What made it difficult to classify peers' messages?
Q5. Were the descriptions of the categories of cognitive presence accurate and distinct?

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Chapter 53
A Paper Recommendation System with *ReaderBench*: The Graphical Visualization of Semantically Related Papers and Concepts

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Abstract The task of tagging papers with semantic metadata in order to analyze their relatedness represents a good foundation for a paper recommender system. The analysis from this paper extends from previous research in order to create a graph of papers from a specific domain with the purpose of determining each article's importance within the considered corpus of papers. Moreover, as non-latent representations are powerful when used in conjunction with latent ones, our system retrieves semantically close words, not present in the paper, in order to improve the retrieval of papers. Our previous analyses used the semantic representation of papers in different semantic models with the purpose of creating visual graphs based on the semantic relatedness links between the abstracts. The current analysis takes a step forward by proposing a model that can suggest which papers are of the highest relevance, share similar concepts, and are semantically related with the initial query. Our study is performed using paper abstracts in the field of information technology extracted from the Web of Science citation index. The research includes a use case and its corresponding results by using interactive and exploratory network graph representations.

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Keywords Paper recommendation system · Scientometrics · Semantic similarity · Discourse analysis

53.1 Introduction

As more and more papers are being published, the need grows for creating a semantic repository with automatically tagged resources facilitating information access. Researchers and learners alike need to stay up-to-date and constantly search for new papers on certain topics as part of their daily activities. Since the daily retrieval of documents from the Internet leads to a data overflow, it is worthwhile to consider new approaches for a more comprehensive analysis of a database of articles.

We propose a model that begins with a corpus of paper abstracts that are automatically tagged and whose results are used for a semantic database for user defined queries. Once a user inputs a query in natural language text, a graphic visual representation of the query and all the related papers is displayed along with a list of related papers ordered by their level of similarity to the input text. In addition, a list of similar topics demonstrating high semantic overlap with the query is provided in order to stimulate the user in his/her research task.

In this paper, we begin by describing related studies that similarly discuss building network graphs for scientific papers. We then describe the methods used to implement the current system as well as a use case, which demonstrates the potential for our system. We conclude by describing possible future improvements.

53.2 Related Work

Mainstream database software based on keyword matching such as *Mendeley* or *DevonThink* can be considered as research paper recommendation systems, whereas more sophisticated approaches already exist [1]. Leaving aside the systems that rely on traditional information retrieval techniques [2], we expose two opposing approaches for analyzing the content of scientific papers: co-citation analysis and semantic analysis. *Co-citation analysis* [3] is a technique that uses citations between different papers to generate a network graph of all the articles from a domain. Two papers are connected within the graph if they share a common citation, while their corresponding links are weighted by the number of related citations. Different algorithms can be applied to the resulting graph in order to determine citation patterns, as well as central and important articles. There are two main advantages to this method: (1) it is very fast to process because the citations are created by the authors, and (2) it can infer the most important articles from a dataset. However, the method does not consider the semantic content of a paper; hence, the results can be misleading when considering that many citations for the same paper can refer to different parts of it, thus reducing the semantic relevance of each citation link [4]. Nevertheless, this method remains a benchmark for the analysis of articles within particular domains as it is widely used in scientometric analyses [5].

Latent Semantic Indexing [6] creates a semantic representation of words and concepts by establishing associations between terms that co-occur in similar contexts. Based on initial training corpora consisting of texts collections, patterns are captured as relationships between terms and concepts contained in similar documents. Therefore, starting from a term-document matrix, a singular value decomposition (SVD) is applied in order to reduce the dimensionality of the representation. Within the resulting vector space, semantic relatedness is measured through cosine similarity between the vector representations of both words and documents. We take this approach even further when semantic similarity is computed within our system as an aggregated cohesion score [7] based on latent semantic analysis (LSA) [8] cosine similarity, latent Dirichlet allocation (LDA) [9] Jensen–Shannon dissimilarity of topic distributions, and WordNet semantic distances [10].

53.3 The Implemented Paper Recommendation System

Our aim here was to extend on the semantic views described in [11] and to create a paper recommender system that enables users to define queries in natural language and retrieve the most relevant papers. This extended model detects the most similar papers within the dataset, based on semantic cohesion, that resemble the input query [7]. In addition, we introduce the idea of generating highly cohesive concepts to the initial query by considering the most relevant keywords from other documents that have the highest semantic relatedness to the input text, a query expansion technique.

In terms of technical implementation, the paper recommendation system relies on *ReaderBench* [7, 12], an advanced text processing tool that has many components including a text processing module that creates a layered cohesion graph used as an underlying discourse structure. *ReaderBench* represents a good starting point as it already has a fully functioning natural language processing pipeline [7, 13] and multiple integrated semantic models covering LSA vector spaces [8], LDA topic distributions [9], and WordNet semantic distances [10], as well as specific Social Network Analysis tools and metrics used for visualization [14].

When a user enters a query in natural language, the input text undergoes the same pipeline as general documents: text preprocessing and cleaning, lemmatization, part of speech tagging, syntactic dependency analysis, and topics extraction [7, 13]. After the input query is represented as semantic vectors in LSA and LDA models, its semantic similarity with each document from the dataset is computed. The resulting cohesion scores are used as measures for creating the links within the interactive and explorative displayed graph (see Fig. 53.1).

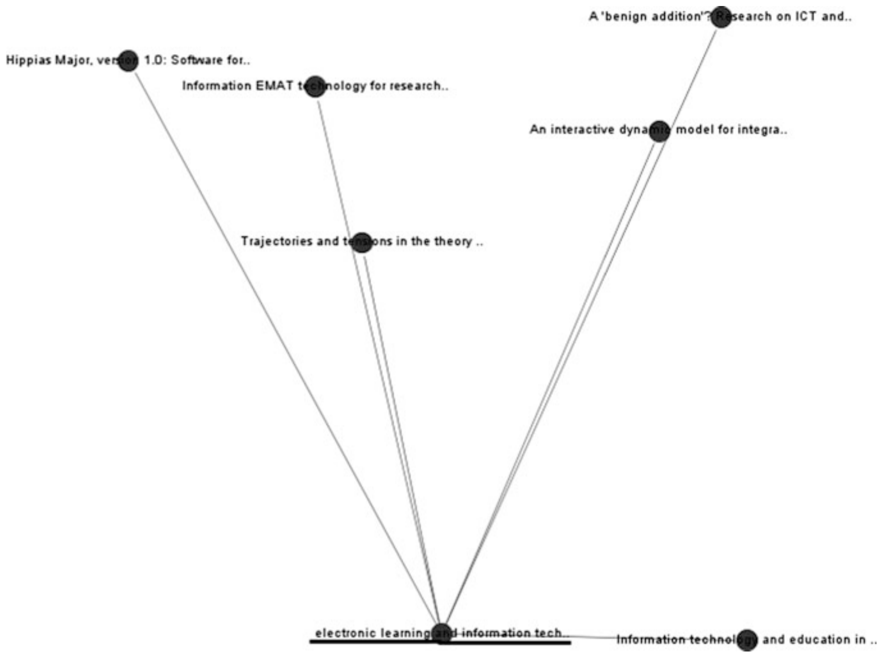

Fig. 53.1 Network graph of the semantically related documents to the input query

Furthermore, in order to stimulate the learner's creativity in terms of query generation, the system also includes a module that extracts the most important topics of semantically related documents from the dataset (not present in the initial query) and computes the semantic distances between them and the input text.

53.4 Use Case

In order to demonstrate the adequacy of the proposed methods, a query example and its corresponding results are described in this section. The database of documents used in the experiments consists of article abstracts published between the years 2000 and 2004 from the Web of Science citation index for the Education and Educational Research [15] domain. From all these abstracts, a subset of 500 papers containing one of the following keywords: "*IT,*" "*technology,*" or "*computer science*" was extracted. In the present example, a user inputs the text "*electronic learning and information technology,*" with the intention of finding papers that are about informational systems within the educational sciences domain. Figure 53.1 depicts a subgraph with the most semantically related articles for an imposed semantic similarity threshold of 60 %.

The three most similar documents from the dataset are "*Trajectories and tensions in the theory of information and communication technology in education,*" "*Information technology and education in the information age,*" and "*An interactive dynamic model for integrating knowledge management methods and knowledge sharing technology in a traditional classroom.*" In contrast to traditional information retrieval systems that focus on identifying the occurrences of each query concept within the retrieved documents and weighting their underlying frequencies, we rely on the similarity of the semantic contexts. This provides a more exploratory approach based on the overall similarity between the query and document representations within each semantic model.

The results of our use case scenario are in the same semantic context as the query and are good indicators that the methods used inside the recommender system can provide reliable and semantically relevant outputs. Moreover, the model recommends additional search terms for the current example such as "learner," "teacher," "science," "curriculum," "research," "process," and "development" (see Fig. 53.2), which are clearly relevant inferred concepts for the query at hand.

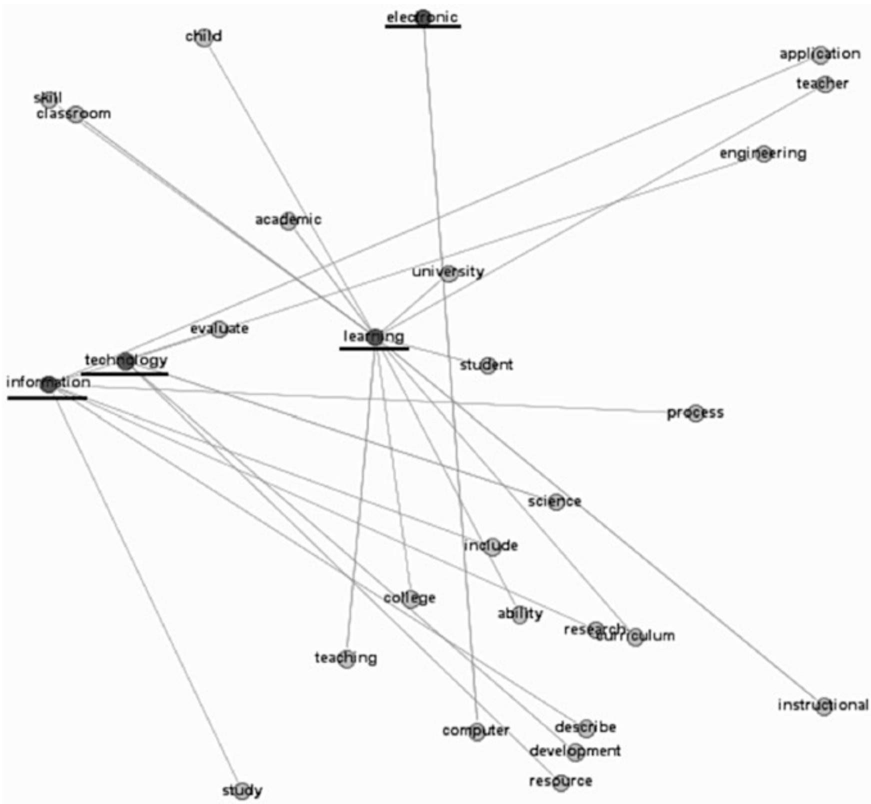

Fig. 53.2 Concept map of query concepts and semantically related words

In addition, we emphasize a major benefit of our method, derived from the use of semantic models for representing each document and the input query. The central concepts from the query become self-emergent as more text is presented and as the semantic context is more clearly specified. In contrast to traditional information retrieval systems in which the user needs to be specific while defining the keywords of the query, this system enables a refined search of semantically related documents and of similar concepts. Therefore, natural language queries describing the context in detail are encouraged in contrast to simple, keyword-centered inputs.

53.5 Conclusions

While publications appear online at an increasing rate, our paper recommendation model can have a beneficial impact for anyone interested in the study of a specific subject or domain and can support the research communities in their endeavors. Moreover, users can further refine their searches by checking various related articles containing keywords that they may not have initially thought of. Therefore, through successive iterations using our recommendation system, the user can become more productive by exploring semantically related articles with diverse underlying concepts. In contrast to information retrieval systems centered on keywords identification, the integrated semantic representations provide a broader view of similar contexts, which in turn have the potential to stimulate creativity.

For future developments, we consider it appropriate to create a topics time-modeling system that generates a temporal view for the evolution of the most relevant paper concepts for a given time frame and the articles' theme. As a drawback, the current model provides timely responses for hundreds or thousands of papers, but does not scale well with a large database of papers because an iterative search is performed throughout all potential documents. Therefore, further system performance enhancements are envisioned by considering the clusters of similar papers as well as the implementation of a hierarchical search.

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Chapter 54
A Tutorial on Machine Learning in Educational Science

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Abstract Popularity of massive online open courses (MOOCs) allowed educational researchers to address problems which were not accessible few years ago. Although classical statistical techniques still apply, large datasets allow us to discover deeper patterns and to provide more accurate predictions of student's behaviors and outcomes. The goal of this tutorial was to disseminate knowledge on elementary data analysis tools as well as facilitate simple practical data analysis activities with the purpose of stimulating reflection on the great potential of large datasets. In particular, during the tutorial we introduce elementary tools for using machine learning models in education. Although the methodology presented here applies in any programming environment, we choose R and CARET package due to simplicity and access to the most recent machine learning methods.

Keywords MOOCs · Educational data mining · Learning analytics

54.1 Introduction

Continuous advancement in data collection and storage techniques changed many industries and research areas. Internet is taking the role of libraries, twitter brings information to public faster than any newspaper, and stock markets are run by high-frequency trading algorithms. In education, still substantial part happens in classroom; however, we also experience new, global initiatives, exemplified by massive online open courses (MOOCs).

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One of the key challenges of MOOC research is closing the gap between educational science and online education [2, 3]. Increasing number of computer scientists and data scientists are trying to solve educational problems without contextual knowledge, whereas educational scientists are often not familiar with modern modelling techniques.

Most of educational experiments were run on small groups of students, often from the same school, sharing similar background. Online education allows us not only to see a bigger picture, with millions of students from all over the world, but also gives us opportunity to approach each of these students individually.

New data streams require new methodology. In classical approach, with, say, 50 students in each condition, we could just apply *t*-test or ANOVA. Since the datasets were small, only the large effects were detectable; so the notion of significance implicitly implied relevance. Conversely, when the number of students is large, we can easily end up in rejecting the null hypothesis and detecting an effect irrelevant in practice. Moreover, in the massive context, predictive models can be more accurate if only associated with large number of valuable variables.

During this tutorial, we present methodology for forming and testing hypothesis in this new setup. We also present practical guidance for building data-driven predictive models with the state-of-the-art machine learning methods (Fig. 54.1).

54.2 Dataset

We use the data from the Introduction to C++ and Introduction to Java offered by the EPFL in the fall 2013. We had 13,787 students in the C++ course and 17,716 students in the Java course. Both courses had very similar structure in terms of number of weeks, assignments, and the abstract object-oriented content.

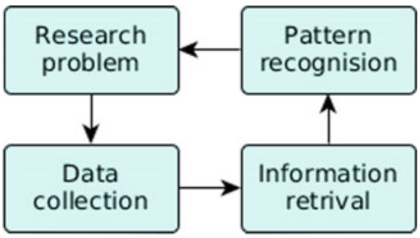

Fig. 54.1 The flow of data-driven educational research is now altered by information retrieval step, where we find an adequate representation of a vast dataset

54.3 Hypothesis

The main step of any analysis is the formation of good questions. Classical experiment design still holds and large datasets allow us to analyze deeper patterns, for example: *to what extent perceived video difficulty is reflected by video interactions (pauses, speed ups,* etc.*)*? [5] or *Does forum activities and in-video interactions reflect decreasing engagement over time*? [9]. In this tutorial, we predict the students' grade based on their temporal behavior. We hypothesize that the model is independent of the course, since both courses have similar structure and they were supposed to deliver object-oriented programing paradigms. We expect students to behave similarly.

54.4 Data Collection

As soon as we have formulated the hypothesis, we start gathering the data to support it. In the online context, we can still use the classical tools (e.g., questionnaires), but also new sources of data are available. We can record, among others: clickstream (sequence of sites clicked), mouse moves, keyboard writing pattern, video interactions (pauses, forwards, etc.), scroll depth and growing amount of other information provided by Web browsers.

In addition, in an experimental setup, we can ask users for access to their cameras or microphones. Increasing popularity of social networks may provide additional information about student's background and social context. Interesting research may arise just from the analysis of these streams of data. We can, for example, assess student's attention from the camera images, leveraging the small sample research [7].

In this work, we analyze student's time series. We will look on the activities of the student over time, we extract information supporting the hypothesis and we build a predictive model. For each student, we have a time stamps of events of following types: *Forum View, Forum Subscription, Thread View, Lecture Re-View, Thread Subscription, Post on Thread, Quiz Submission (Video), Quiz Re-Submission (Video), Assignment Re-Submission, Thread Launch, Quiz Re-Submission (Quiz), Forum Upvote, Quiz Submission (Quiz), Forum Downvote, Lecture Download, Lecture Re-Download, Comment on Post, Quiz Submission (Survey), Quiz Re-Submission (Survey), Lecture View, Assignment Submission, Registration*.

54.5 Information Retrieval

After gathering the relevant data, we extract features important for the research question. First, we extract simple characteristics like the number of the following: videos watched, posts written, and posts read. Next, we add more sophisticated constructs. To that end, we use the existing domain knowledge and we explore the dataset.

In our context, visualization of a students' time series may give us insights about how to extract variables as illustrated in Fig. 54.2. We can also look for well-establish constructs, defining, for example, *Procrastination* as the number of times a student submitted the assignment just before the deadline, *Persistence* as the number of retries of assignment submission, or *Regularity* as the variance of difference between two watching sessions.

As an output of this step, we have a large structured table, with one row per each student and extracted variables. In the next step, we use this table for training machine learning models.

54.6 Pattern Recognition

We identify two main branches of machine learning: supervised learning and unsupervised learning. The goal of supervised learning was to identify patterns within independent variables to explain a dependent variable. The key example here is the linear regression and logistic regression, known from classical statistics. Recent techniques such as support vector machines [1], random forests [6], and generalized boosted regression [8] are gaining popularity due to their robustness,

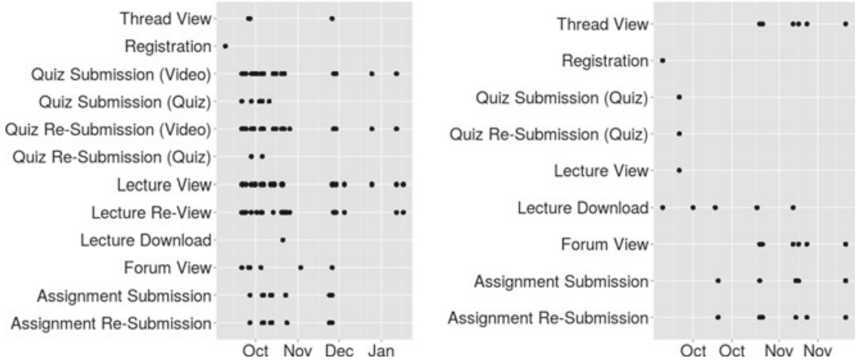

Fig. 54.2 Visualization of time series of two students, one who succeeded with 87 % points (*left*) and one who failed with 66 % points (*right*). Although both of them completed the assignments, the left one was clearly more engaged. Observations from visual assessment can help us to engineer variables informative in the given context

computational feasibility, and effectiveness. The unsupervised learning, whenever there is no dependent variable and we want to investigate patterns in the data, most commonly clusters *similar* observations.

For our example, we use supervised learning to predict grades of students. To this end, we represent each student as a vector of his characteristics as described in Sect. 54.5. To fit the model to the known instances from the training set, we need an accuracy measure. In our example, we use the root mean square error, which, intuitively, expresses the mean distance of the prediction to the observed value.

Listing 54.1 presents a process of model building using the dataset with features described in Sect. 54.5. We use a very convenient R framework CARET [4] for application of machine learning methods. In particular, to choice of the underlying supervised learning technique is govern by method and with method = “rf” we apply random forests instead of SVM. This allows us to quickly prototype and to compare models.

Since over 90 % of students dropout out before finishing any assignment, prediction of their score equal to 0 is easy, and therefore, we focus only on students who achieved at least 10 % points from the assignments.

To asses the quality of various models, we look on the estimated RMSEs. The simple commands to compute and plot these values are presented in Listing 54.2, where we assume that models model.svm, model.rf, and model.gbm were build as described above.

The best model, generalized boosted regression, achieves RMSE around 13 as presented in Fig. 54.3. We consider this result satisfactory, taking into account simplistic, illustrative approach.

Exploratory data analysis [10] can be useful for finding an appropriate technique, for adequate data transformation, for outlier detections, etc. Moreover, this exploration brings new insights and hypothesis and eventually closes the cycle in Fig. 54.1.

```
library(caret)
# Build the model
control <- trainControl(method="repeatedcv", number=10, repeats
    =3)
model.svm <- train(Grade ~ ., data=students.tr, method="
    svmRadial", trControl=control, tuneLength=5)
# Predict the grades
grades = predict(model, students.ts)
```

Listing 54.1 Building an SVM model using the CARET package in R

```
results <- resamples(list(svm = model.svm, rf = model.rf, gbm =
    model.gbm))
# boxplots of results
bwplot(results)
```

Listing 54.2 Comparison of performance of different models

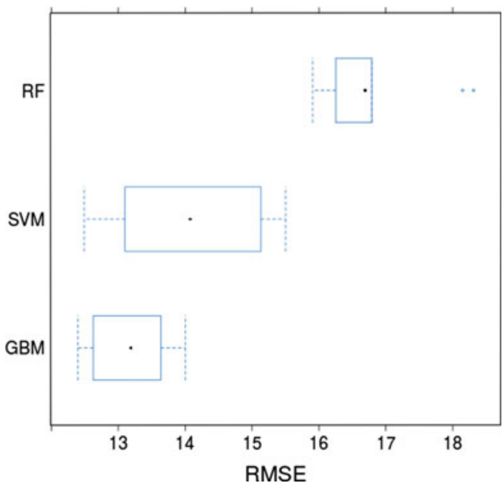

Fig. 54.3 Errors of each model in terms of the RMSE

54.7 Discussion

The analysis of educational data in the massive context requires new techniques and methodologies. The goal of this tutorial was to shed light on the usage of machine learning and the process of the analysis, in the context of online education. Since it is not possible to introduce advanced techniques in details during a short tutorial, we focused on illustrating the simplicity of application of state-of-the-art machine learning using the R package CARET.

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Chapter 55
A Smart Environment Supporting the Creation of Juxtaposed Videos for Learning

Nils Malzahn, Elizabeth Hartnett, Pablo Llinás and H. Ulrich Hoppe

Abstract This paper presents the JuxtaLearn approach to stimulate creativity and engagement in areas of science, technology, engineering, and math (STEM) by guiding the students through a process aiming at the creation of videos on a specific STEM topic. The students are asked to juxtapose their understanding of the topic with creative expression in the form of video performance. This approach is expected to trigger transformative learning. The JuxtaLearn process is supported by the JuxtaLearn system (ClipIt)—a smart environment that supports the students during the different stages of the learning process. We report on findings related to the usage of specific support tools derived from case studies. We further explain how these insights are cast into technology support.

Keywords Video-based learning · Transformative learning · Technology support

55.1 Introduction

The ongoing European project JuxtaLearn aims at fostering learning in different fields of science (or STEM) by combining curiosity and understanding with performing. Concretely, the students' performance is substantiated in the form of creative video making and editing activities. We see this way of learning by performing

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and presenting as a variant of Papert's "constructionism" [1] and as similar to learning by teaching [2]. In this context, we are interested in studying the role of video as a medium for learning in different (including passive) forms of usage.

Drama, as opposed to theater, is about a performance process, not a product [3]. Pioneers in educational drama such as Peter Slade, Eric Bentley, and Brian Way [3–5] developed activities based on drama improvisation. Yaffe [6] outlined the advantages of drama as a teaching tool and a means of juxtaposing other classroom subjects over 20 years ago, and so did Dorothy Heathcote before that [4, 7]. Dorothy Heathcote's work encourages reflective moments using drama, not to produce plays, but to expand awareness, enabling students "to look at reality through fantasy" [7]. Drama enables students to use what they already know, to achieve something that cannot be attained as effectively in other ways. The scientist suddenly sees an analogy in something that influences his or her imagination. Hence, Watt watched his kettle steaming and raising its lid giving him the idea for the steam engine [8]. This story provides the analogy that explains the science.

We tell stories as a means of understanding the world around us [9], a means for making sense of what we experience. Hence, the JuxtaLearn process encourages students to tell stories that make sense for them of a STEM tricky topic.

We take the idea of a tricky topic from Mayer and Land's threshold concepts [10, 11]. Threshold concepts (TC) show characteristics of being transformative, irreversible, integrative, bounded, and troublesome! While Mayer and Land have identified TC, the teachers in our JuxtaLearn trials talk about topics that are difficult to teach, or that the students find tricky. Hence, in this paper we refer to tricky topics.

JuxtaLearn is about the process of learning through performing. Research evidence already exists that supports drama's inclusion in education curricula [12, 13]. The DICE consortium reports results from a comparatively recent EU-supported project. It provides evidence across 12 countries of the benefit of drama in the curriculum and shows how drama use in education increases key competences. However, it does not look specifically at the juxtaposed use of drama to support learning in STEM subjects, which is what JuxtaLearn does. Therefore, we designed JuxtaLearn workshops that used dramatized activities to support learning in STEM subjects. A JuxtaLearn workshop builds on a teacher's initial identification and demonstration of a tricky topic (Steps 1 and 2 in Fig. 55.1). The students then interpret the topic and take a quiz on it before moving on to the performance stages of the process. These later steps form a JuxtaLearn workshop or series of workshops, the process being sufficiently flexible to take a day or a series of lesson slots.

55.2 The JuxtaLearn Process

Juxtaposing happens when two unlike ideas are placed side by side, forming a contrast and highlighting the differences. We see juxtaposed learning as an educational approach built on pedagogies of threshold concepts and collaborative learning. We are using a working definition of juxtaposed learning as follows:

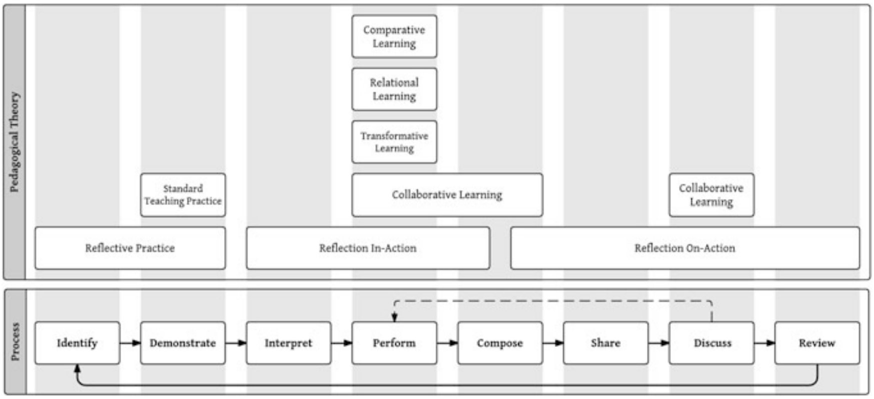

Fig. 55.1 Stages of the JuxtaLearn process and their respective learning theories

"Juxtaposed learning involves learners studying material and then in peer groups, creating a different and contrasting presentation or performance of the material."

Performance is central to JuxtaLearn's objectives of both inspiring curiosity through creative film making and sharing activities and supporting understanding of threshold concepts by scaffolding personalized conceptual needs and reflections between formal and creative juxtaposed applications of these concepts.

Threshold concepts [10, 11] have become a focal point for understanding conceptual barriers to understanding. Their research has pointed toward TCs as a starting point for transformative learning [14]. However, this concentrates on the content and understanding. There are arguments that highlight the need to focus on effective methods for teaching threshold concepts [15]. Within JuxtaLearn, young people are engaged in learning by harnessing their abilities to create "juxtaposed" engaging video representations of concepts. This juxtaposing of student-directed inquiry and creativity with formal representations of understanding lies at the heart of the JuxtaLearn process and its transformational power. Educationalists have long recognized that transfer of learning is the most significant issue in teaching and learning. It not only supports application to various different questioning approaches that may occur in an exam, but further the question of durable transfer to lifelong learning situations such as in the workplace. Technology-enhanced learning which facilitates this transfer can transform students' learning. Haskell [16] presents experimental evidence of transfer as a neurocognitive mechanism that is the basis of learning from mental abstractions and analogical relations to the ability to classify, generalize, and develop logical inferences. However, there has been much debate about the success of any educational method in providing this durability and transferability. This transfer of learning is done within JuxtaLearn Steps 3, 4, and 5 (see Fig. 55.1) through comparative learning methods with students directly comparing, for accuracy, their creative interpretations of tricky topics (i.e., teacher defined threshold concepts) against teachers' traditional constructed representations:

Stage 4 Perform: collaborative "reflection-in-action" through co-creation of storyboards. Technical support systems like a storyboard tool on tablets or tabletops that scaffold the students to keep focusing on their task: explaining tricky topics rather than performing any type of good video.
Stage 5 Compose: collaborative "reflection-in-action" through the group-based selection and composition of video footage into a finished video.
Stage 6 Share: Sharing and commenting on the video results enhances collaborative "reflection-on-action" through discussions with peers that allows them to re-evaluate understanding.
Stage 7 Discuss: Large screen displays provide yet again a review of the experience with "reflection-on-action" while also providing in the quizzes a means to test internal consistency.
Stage 8 Review: Learning analytics throughout the latter "reflection-on-action" cycles provide teachers and students with evidence of group progression and internalization of understanding enabling further knowledge to be built upon strong foundations.

Christie and Gentner [17] identify statistically significant advantages to developing understanding and meaning making through direct comparisons. They reviewed how we effectively develop these understandings and the learning processes through direct comparison. This has since been expanded upon by Kurtz et al. [18] to highlight the value of comparison to promote learning and transfer of relational categories with undergraduate students. Reflection is a route to supporting this in the learning process. JuxtaLearn therefore utilizes reflection throughout each stage of the learning process both informally through peer refection during the creation process and formally with technology support on reviewing the artefacts after their creation.

55.3 Empirical Findings

55.3.1 Experiment Setup

We conducted three JuxtaLearn workshops at a secondary school, with students with an age of 16–19 studying or starting to study A-levels: two chemistry workshops and a non-STEM subject (theater studies). Those allow us to compare the two STEM workshops with the theater studies workshop, thus being better able to identify and demonstrate how the JuxtaLearn process motivates students to overcome barriers to understanding of complex concepts. Each of the workshops was conducted within one day. Table 55.1 shows an: a example timetable of activities.

Table 55.1 An example timetable of activities

Time to allow	Activity	Resources
1 day	Teacher prepares, presents or provides students with material that introduces the tricky topic	Presentation, pencast, textbook, videos
20–30 min	Recalling the tricky topic Initial quiz of understanding of the tricky topic	Computer and Internet access to ClipIt Web site
10–15 min	Discuss how to juxtapose in performance by choosing a setting and characters	
60 min	Collaborative development of storyboards: Discussion of ideas about the tricky topic, its relation to their performance ideas. Teacher observes and advises on the topic's stumbling blocks	JuxtaLearn storyboards either on paper or table top
30–60 min	Teacher and groups discuss potential performance in relation to the stumbling blocks Preproduction within groups, e.g., allocate roles, find assets, decide location, with reference to the storyboard	Storyboards
60 min	Video production Refinement of storyboards	Video equipment, e.g., flip cameras/smartphones
30–60 min	Post-production composing: compose shots to match storyboard. Edit shots as necessary. The group reflectively discusses how it explains the stumbling blocks, checking with the teacher, and reshooting if necessary. At this stage, the group might also want to voice-over a script, or add text	Editing software, video software
10–20 min	Have a class discussion of progress so far, of what their stories are so far, and if any videos are partly ready, then to look at the first cuts	Large screen for sharing, camera connectors, computer
30 min	For post-production, composing scenes to match storyboard and editing, doing retakes cutting down, assembling and retaking some scenes if necessary to make the story clear and short (3–5 min)	ClipIt, editing software
10–20 min	Class discusses and shares students' videos, and feedback on their learning	ClipIt

The table refers to JuxtaLearn storyboards. A storyboard is a visual plan for a film, and a JuxtaLearn storyboard is adapted specifically to the JuxtaLearn process by including a list of stumbling blocks on one side as prompts to guide the students (see Fig. 55.2).

55.3.2 *Findings*

Our use case workshops generated observational data together with focus group and interview feedback.

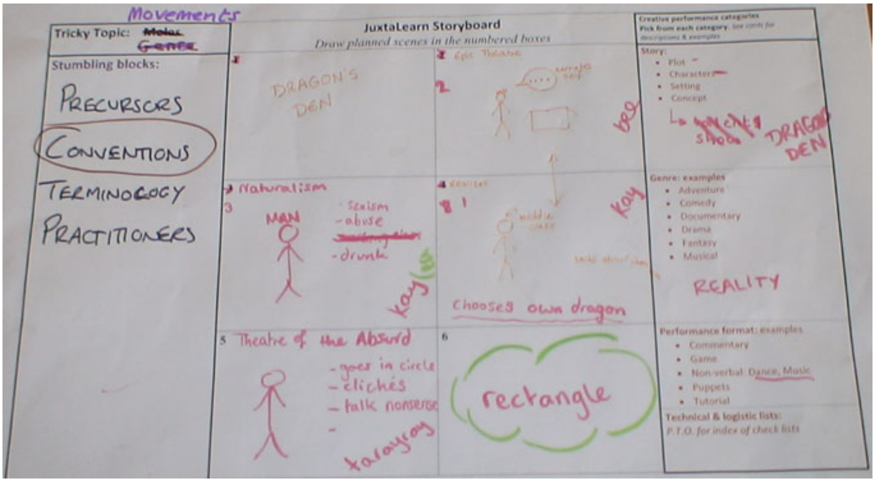

Fig. 55.2 Example paper storyboard used in chemistry

Contrasting STEM to Drama we found that theater studies students see themselves as creative already. Multi-colored penned words represented abstract ideas on the all-girls paper, biro crossings-out and stick men on other papers.

Moreover, they were not audible, neither when performing, nor when discussing. However, eventually, their teacher arrived and discussed with them theories of naturalism and realism, also suggesting they found somewhere quieter to record. That hour was the students' learning hour, the hour when they stumbled, fumbled, and realized that they did not know.

Students from the sciences liked the term "presentation" better than performance. They tend to see themselves as technical and geeky, not as creative or performers. Additionally, these students were confused by the word "story" at early stages, whereas they had an intuitive understanding of the word "presentation."

A group still developing their ideas played walking their fingers in front of the camera. At first this was social play, but half an hour later this group was developing little characters of Plasticine, walking them across the same desk for the camera. Thus, it seems reasonable to plan the activities in a way that allow playing time for sowing and germinating ideas.

Finally, one of the teachers commented: "Last time we had a professional film crew and it was all very jazzy and fun. It was enjoyable but nobody got any real learning out of it in terms of deep learning, whereas this time it was simple hand held things. And the focus has been on understanding stuff. So removing the flashness of the technology has helped."

55.4 Discussion

The school trials identified the true complexity and difficulty for the students in the activity of juxtaposing their learning and demonstrated a need for a structured approach to the juxtaposing process.

How to juxtapose became a barrier to the students moving forward in the JuxtaLearn process. While the process had intentionally kept the juxtaposing and comparative learning open to increase the space for students' creativity at first, however, we observed that the creative process needs guidance because the students were required to take creativity into a field where they did not normally learn through creative approaches.

Where juxtaposing worked, students started with characters, not story. Observations from non-JuxtaLearn workshops revealed the drama teachers first helped students to develop characters and settings before other aspects of performance; find the character, then the setting seems to drop into place, and the plot unfolds. For example, in chemistry where the topic is molecular mass of water and carbon dioxide students took the moles' atoms and had them as different characters personified as animated blobs of plasticine. Obviously students need scaffolding for the process with a simple yet flexible structure to juxtaposing.

Neither students nor teacher saw the storyboard as important, although the storyboard was referenced as an object of discussion in studies that were running more than one day. The storyboard guides them through development and pre-production, e.g., go and source those costumes and later in post-production, put them in sequence even if you did not produce them in sequence, so the storyboard is a creative tool that can be used to manage the project.

The orchestration of the whole learning process stays with the subject teachers. They need to support the students, if they struggle to understand a specific theory or connection between a pair of domain concepts.

Thus, both the teacher and the students need support conducting the complex process. For this purpose, we have developed the JuxtaLearn system that is described in the next section.

55.5 ClipIt—A Smart Environment

The JuxtaLearn system comprises a set of software tools that is running on a variety of technical platforms (see Fig. 55.3). If not all platforms are available at a particular site (e.g., no multi-touch tables), a Web browser on a standard PC is always a fallback option to continue the process.

Thus, the heart of the system is built by ClipIt [19]—a Web-based system built upon Elgg[1]—a social media community framework. Within ClipIt, all resources

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[1] http://www.elgg.org (Accessed 1 June 2015).

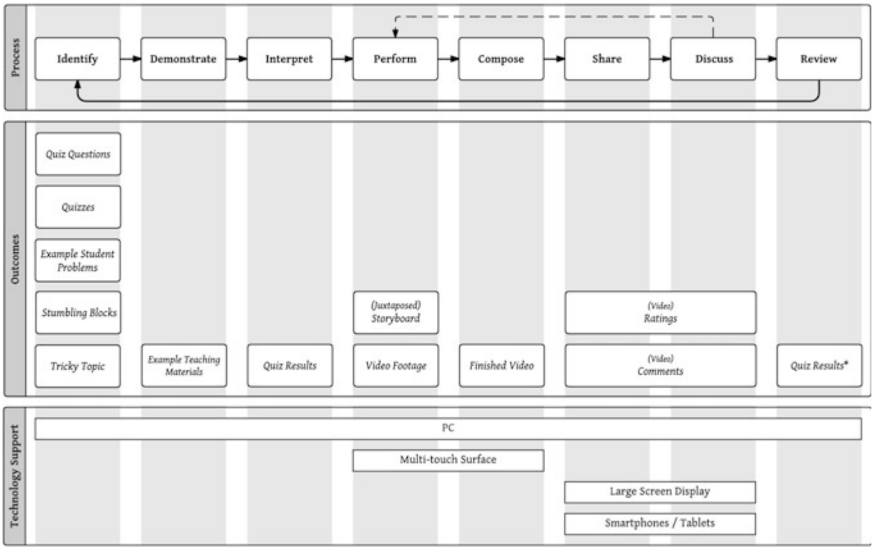

Fig. 55.3 JuxtaLearn systems distribution of resources over stages and platform

produced during the JuxtaLearn learning process are stored and may be retrieved by other components of the JuxtaLearn system via REST Web services. We have identified the need for special support for teachers and students during the video creation phase (perform/compose) and are therefore developing an interactive storyboard that supports the students by prompting them to, e.g., name the characters and assign the stumbling blocks of their activity to the scenes they have developed. This guides the students through the process of developing storyboards without restricting their creativity too much. When students upload their video footage, they are also asked to assign stumbling block tags to them so the system later on gives feedback on the overall coverage of stumbling blocks within their project. This keeps the students' focus on the stumbling blocks and reminds them of the whole set of them needed to understand a particular tricky topic.

Furthermore, depending on the state of the current progress in the learning process, the system offers recommendations with respect to additional learning resources. For example, during the interpretation phase the system recommends additional material depending on the student's knowledge profile derived from quiz results and (if available) ratings by their peers on their published videos. During the perform stage of the JuxtaLearn learning process, related storyboards from other groups may be suggested as a source of inspiration.

While the above functionality helps the students to keep on track and improve their understanding, teachers need some support as well. This is especially true if the process is not entirely conducted within classroom sessions. For this purpose, ClipIt provides a teacher's dashboard (cf. Fig. 55.4) that provides awareness meters.

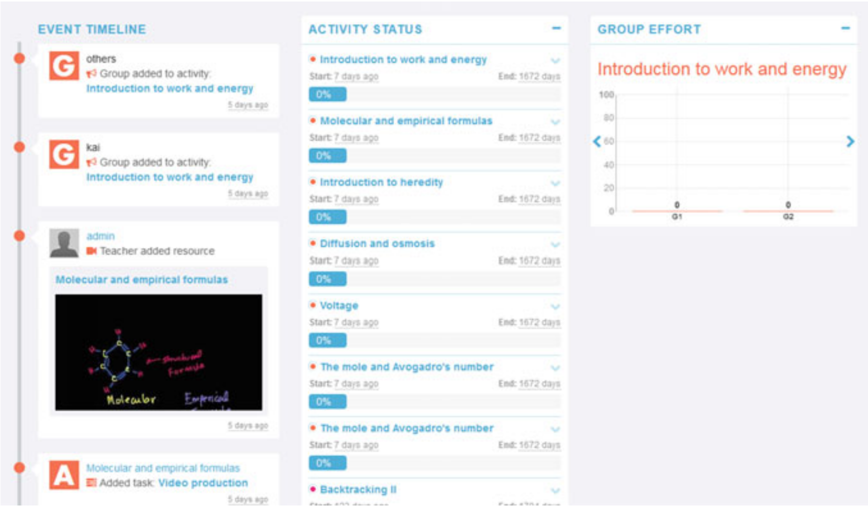

Fig. 55.4 ClipIt landing page with information about the general progress (teacher view)

The teacher's cockpit comprises tools for the supervision of the whole process. Among others, there are tools that allow for the comparison of quiz results (optionally aggregated per student group), the group's progress through the steps of the JuxtaLearn learning process and the collaboration quality. The latter is presented by a network view of the collaboration process based on communication in discussion forums and uptake of each other's work.

In summary, ClipIt tries to support the creative process of the students by providing helpful information for the task at hand and keeping the teachers informed about the students' progress and problems to allow for early intervention as an additional means of support.

55.6 Conclusion

The JuxtaLearn approach of teaching STEM topics by guiding the students through a learning process that uses video production and juxtaposition is a teaching strategy that produces promising results. Obviously, there are differences between the two subject groups (drama students vs. science students) in their perception of the task and their general attitude toward creative play, but this did not impact the overall outcome with respect to learning. However, we identified character generation as an important ingredient for successful juxtaposition of the subject matter. Thus, in future work we will try to improve the support for character generation during the process.

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Chapter 56
An Interactive Video-Based Learning Environment Supporting Learning Analytics: Insights Obtained from Analyzing Learner Activity Data

Alexandros Kleftodimos and Georgios Evangelidis

Abstract Online videos are extensively used in education, and a recent trend is the integration of interactive elements and Web content into educational videos. This paper describes in brief how open source tools can be used for developing learning environments where video content is aggregated with interactive elements, educator content, and content coming from open Internet resources. It also describes how such tools can be used for capturing and storing learner activity data which can then be used for data analysis and data mining purposes. Finally, the paper presents insights obtained from analyzing learner activity data, gathered over a semester period.

Keywords Interactive educational videos · Video learning analytics · Open educational resources

56.1 Introduction

Online educational videos are mostly linear videos that are watched passively with the only means of interactivity to be limited to the navigational buttons used to start, pause, and resume the video. Recently, a new array of tools have appeared for adding interactive elements and extra content to educational videos, such as EDpuzzle (http://edpuzzle.com), eduCanon (http://www.educanon.com), and Zaption (http://www.zaption.com). Zaption, for example, is a platform that allows the educator to

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choose videos from the Web and add content such as basic text and image slides and interactive elements such as open responses, multiple choice questions, check boxes, drawn responses, and numerical responses. The content and elements are added at certain points in the timeline through a drag and drop interface to create a time-based interactive video. Discussions can also be accommodated in a video, a feature that also exists in other platforms such as Vialogues (http://vialogues.com) and Grockit answers (http://grockit.com/answers). Learners can submit questions about the video content at any point in the timeline or give responses to other learners' questions. Popcorn Maker (http://popcorn.webmaker.org) is another tool which is used to remix Web video, audio, images, and content coming from Internet recourses and Web services in order to create an educational mash-up.

There are many features that could be supported by such interactive applications, but the aforementioned applications contain a different subset of the possible features. Furthermore, most of these applications are commercial (e.g., Zaption, Educanon) and do not offer all the features for free. Another drawback is that none of the above tools are open source (besides Popcorn Maker), meaning that these tools are not open to further development or customization by independent developers.

As far as learning analytics are concerned, some of these tools provide basic-level options mainly through visual reports (e.g., eduCanon, Zaption). Analysis of video-viewing data is a relatively recent trend, and there is a small but significant body of on-going research that focuses on the topic (e.g., [2–4]). Thus, it is certainly a plus for a tool to provide advanced analytics features as well as the whole dataset for further data analysis and mining.

In Sect. 56.2, we describe how open source technologies and open Internet resources are used to create a learning environment where interactive elements, user content, and Web content are aggregated with educational videos in order to transform the video-viewing process into a more interactive experience. In Sect. 56.3, we describe a module for gathering and storing viewing activity data for data analysis and data mining purposes. Details of the educational settings together with findings obtained from analyzing learner activity data are presented in Sect. 56.4. The aim of the data analysis was to obtain insights on how the learners used an educational video and the available navigational features within the environment, throughout a semester period, and to investigate whether educational video viewing has better learning outcomes when accompanied by other activities such as assignments related to the video content. The paper concludes in Sect. 56.5.

56.2 Developing a Video-Based Learning Environment Using Open Source Tools and Open Internet Resources

After conducting research in order to spot open source technologies that can be used to develop time-based interactive videos we recorded two available options, the Mozilla Popcorn framework (used in Popcorn Maker and Grockit Answers) and open source HTML 5 players such as Media Element (http://mediaelementjs.com) and Flowplayer (http://flowplayer.org).

To build the application that we have used in educational settings, we used Media Element, an HTML5 player that can be used for videos that are hosted on a Web server or can act as wrapper for videos hosted in YouTube and Vimeo. By using the API of Media Element (or similarly the API of the other mentioned tools), actions can be initiated when specific time points (or intervals) are reached in the video timeline or when certain video events occur (e.g., pause, resume, start and end of video, volume change). A typical action is the retrieval (or storage) of content from (or to) a database and this is the basis for building time-based interactive videos.

The main feature of the application is the existence of two modules. The first is the "Administrator Module," where various elements are defined by the educator at various time intervals or points. The elements can then be previewed by executing the video and are finally stored in the database if the result satisfies the educator. If the result is not satisfying, the elements can be deleted or altered. The other module is the "Viewer Module." This is used by learners, and in this module, the elements are retrieved from the database and presented to the learner at the specified time intervals (or time points) during video execution.

Javascript (and Jquery) is used in the front end of both modules. More specifically, it is used to track video time and video events and for handling input coming from the educator (e.g., insertion of multiple choice questions) and the learner (e.g., submission of answers). To store and retrieve content from the database, PHP and MySQL are used.

The features that are present in the learning environment are the following:

(a) **Questions that appear at various points in the timeline**. Quiz question elements can be defined and stored in the database by the educator. These are then retrieved when the learners view the video (in the Viewer Module). The quiz questions appear when the player head reaches specified time points. So far we have implemented quiz questions and open response answers, but other types of questions can also be implemented.

(b) **Sections and the Table of Contents**. Very often it is useful to segment an educational video into sections where each section covers a particular subtopic. Then, the learner can be provided with a table of contents. This feature aids learner navigation and is particularly useful for long videos. Furthermore, the breakdown of multimedia in logical segments is supported in the literature [6] as a way to make multimedia learning more effective and is referred to as the "segmenting principle."

(c) **Subtitles**. There is a vast range of educational videos on YouTube or Vimeo, but these videos are mostly in English. To be used in countries where English is not the native language, the educator can carry out the subtitling process by setting the relevant subtitles at specified time intervals. Then, during learner viewing these subtitles are fetched from the database and shown in a text box underneath the video.

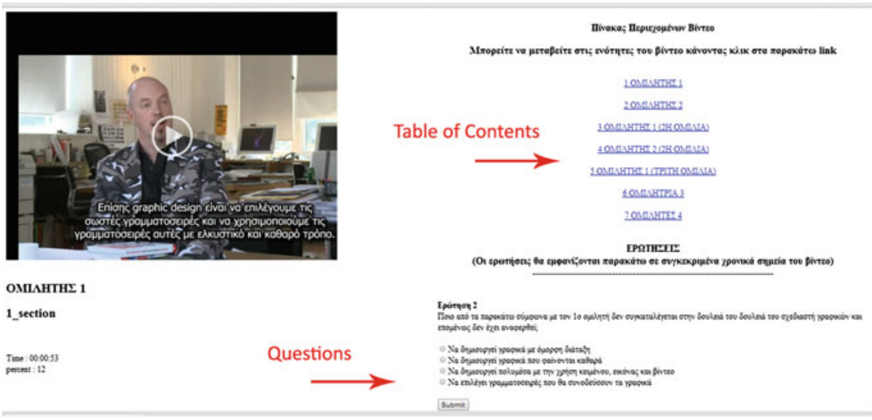

Fig. 56.1 A snapshot of the learning environment where an educational video is used to support the course "Graphic Design"

(d) **Content aggregation**. Another feature is the integration of Web content to educational videos. More specifically, Web content coming from Web pages and Web services can appear next to the video. Using the Administrator Module, the educator defines the Web pages that will appear when the player is within certain time intervals. The Web pages will appear next to the video either as links (and the learner will have to follow the links) or as embedded Web pages in an iframe (e.g., Google Map, Google forms). Another useful option is the synchronization of an educational video with content coming from Web services. This is achieved with the parallel use of the Media Element API and other Web services APIs. For example, in the developed learning environment, video content can be synchronized with slides from Slideshare (http://www.slideshare.net).

In Fig. 56.1, we can see an instance of the environment where two of the above features are used (i.e., table of contents and questions).

Furthermore, using the same mechanism, where various elements are stored and called from the database at specific time points, other features can be facilitated also, such as learner video annotation and discussions. The incorporation of these features within the application is under development.

56.3 Video Learning Analytics

In the heart of the learning environment lies a module with the task of collecting and storing learner viewing activity for data analysis and data mining purposes. The module consists of a program that tracks and stores video events that are triggered by learner actions and changes in the video state. A database with a suitable schema is used for storing all the relevant information.

Learners are required to perform a login procedure to be able to view the videos. All the activity data stored is then associated with the current learner id and is not anonymous. It is also possible to associate the collected data to IP addresses rather than user ids if ethical issues are raised.

In the application database, viewing data are stored in three tables (a) **Sessions**, (b) **Session_videos**, (c) **Session_events**. The database schema is an extended version of the schema presented in [5]. A session starts on learner login and at that point an entry is stored in table **Sessions**. Videos started within a session are associated with the specific session and stored in the table **Session_videos**. Similarly, events triggered during video execution are associated with the particular video and stored in table **Session_events**. Date and time are stored for all the database entries. The same database schema can also be used to accommodate viewing activity data if a different technology is used (e.g., Flowplayer, Adobe Captivate [5]). The tracking program, however, will need to be specific to the technology used and its underlying API function calls.

The events that are specific to the Media Element API and are used in the module for tracking learner activity are the following: (a) **loadeddata**, called when the video is loaded, (b) **seeked**, called when the learner "seeks" by moving the video progress (or slider) bar, (c) **play**, called when the video starts playing or resumes after a pause, (d) **pause**, called when the video is paused, (e) **ended**, called when the video reaches its end, (f) **volumechange**, called on volume change, and (g) **muted**, called on sound mute. A set of properties can be retrieved when these events occur such as the video time, the current date and time. The full list of properties and events is provided in the Media Element Web page.

The database also contains tables to accommodate administrator–educator and learner input (e.g., questions defined by the educator, answers given by learners, subtitles, Web content—urls and embedded code—and topic sections, again, defined by the educator).

Another feature that plays role in analytics is sections. As already mentioned, sections defined by the educator reflect different conceptual topics. Sections can also play the role of marker points in the video. When a marker point is reached, an entry is stored in the database together with the current date and time. Another way of splitting the video is through equal time intervals (rather than different conceptual topics). In this case, the markers are inserted in equal time intervals. The time interval is again set by the educator and stored in a general parameters database table.

The insertion of cue markers that initiate events (section enter event), which are then stored in the database together with other events (e.g., pause, resume), can give us a good estimate of the video portions viewed and provide us with a dataset of viewing behaviors that can be used for data analysis and data mining purposes.

Currently, in the developed application we use both markers for topic sections and markers for time intervals. Although this causes more database accesses (and scalability problems are possible), we concluded that this option is necessary for Media Element in order get more accurate approximations for the segments viewed by learners.

By storing all these events, we obtain a very rich database of learner viewing activity. The acquired data can then be processed and analyzed by using a variety of open source packages, such as R and Weka. At the moment, the environment does not incorporate data analysis modules, but once research confirms the usefulness of certain data analysis tasks the incorporation will take place.

In the following section, we describe the educational settings in which the environment is used and present insights obtained from analyzing activity data using graphical representations and statistical methods. The purpose of the research conducted is to understand the activity behavior of the learners with respect to the environment features in use (e.g., table of contents) and other factors that affect the viewing behavior (i.e., assignment and examinations), throughout a semester period. The analysis also investigates if more active ways of learning such combining video viewing with parallel completion of a related assignment benefit the learning process.

56.4 The Educational Settings and Findings

The developed learning environment is used at the Department of Digital Media and Communication at the Technological Education Institute of Western Macedonia, Greece. The application was first used in the autumn semester 2014–2015 to support the theoretical part of the first semester courses "Introduction to new Technologies in Communication" (5 videos from YouTube) and "Image and Video editing Principles" (1 video, Fig. 56.2). It is also currently used in the spring semester 2015 to support the second semester course "Graphic Design" for both the

Fig. 56.2 A snapshot of the learning environment where an educational video is used to support the course "Image and Video editing Principles"

theoretical part (1 video from YouTube, Fig. 56.1) and the laboratory part (10 videos for learning the vector graphics software Inkscape).

Part of the syllabus is covered by the videos. The features activated in the application for the courses are the following: (a) **Table of contents**, for the courses "Image and Video editing Principles" and "Graphic Design," (b) **Subtitles**, for the course "Introduction to new Technologies in Communication," and (c) **Questions** (multiple choice and open responses) for the theoretical part of the course "Graphic Design." The data recording module is activated for all the lessons mentioned above (theoretical and laboratory).

During the autumn semester 2014–2015, students attending the course "Video and Image editing Principles" were given a video to watch as part of the syllabus. The video length was about 30 min, and it contained information about the promotional video creation process as well as the professionals involved in this process (script writer, director, video editing specialist, etc.). The video also contained interviews with such professionals. The video had been produced by a student with a professional experience in the field as part of his thesis.

Students were given an optional assignment that was related to the video. The assignment consisted of two parts, a questionnaire (20 %) that was delivered through Google Forms and a written assignment (80 %) that consisted of several open-ended questions. The assignment was not incorporated in the video environment but was distributed through the institutional learning management system. The video content was also included in the examination syllabus and students were notified that some questions in the examination would be related to the video content. Indeed, half of the questions in the examination were associated with the video.

Sections were defined for the video and the headers of these sections appeared as a table of contents next to the video (Fig. 56.2). The video consisted of 14 sections. The sections reflected different topics (e.g., an interview). The learners were able to use the table of contents to navigate directly to the specified sections. They were also able to use the typical player buttons (i.e., pause, play, mute sound)

In Fig. 56.3, we see some temporal aspects of the learner viewing behavior. Figure 56.3a represents the views in the time interval from the time that the video was delivered to the students until the examination.

In Fig. 56.3a, we can clearly see two peaks, one before the assignment and another before the examination. We can also see that there are views in the period before the peak related to the assignment, but almost no views in the period between the assignment deadline and the peak related to the examination. In Fig. 56.3b, one can also see in a relative scale the views but also the number of pauses as well as the clicks in the table of contents. From this representation, one can clearly see that the table of contents received more clicks during the assignment period.

Another aspect that we focused on is the section transition matrix. By the term section transition matrix, we mean a table depicting the number of transitions (or jumps) from section to section. Transition matrices can be obtained through various ways. We used (a) the TraMiner package within R and the seqtrate function,

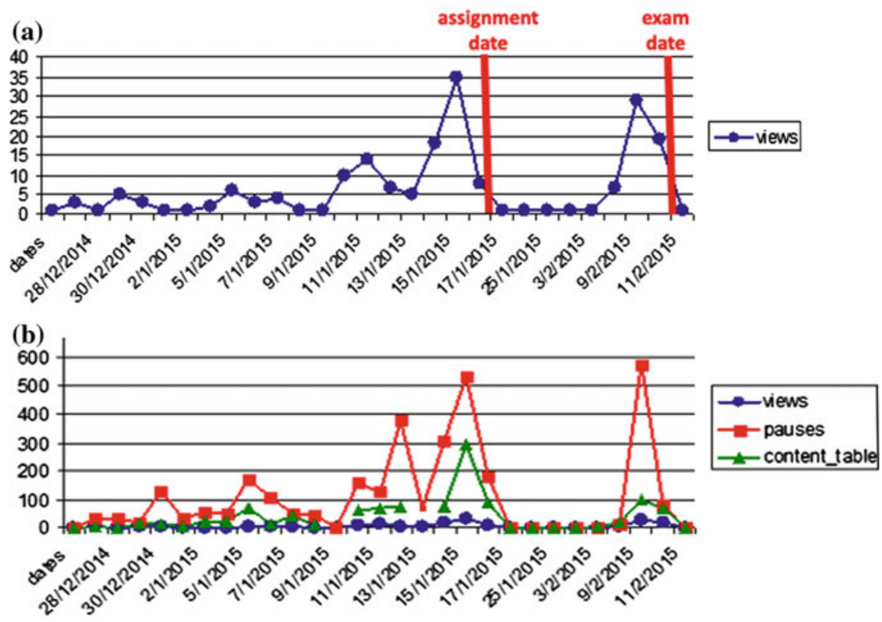

Fig. 56.3 Views and actions

to obtain a table of transitions and (b) the Heatmap2 function of R to obtain a graphical heatmap representation of the transitions. In this investigation, we excluded transitions from one section to itself (e.g., section 1 to section 1) that typically occurs via a pause/resume action within a section.

The most typical transition that can be encountered in a transition matrix is the transition from one section to the section that succeeds it (e.g., section 1 to section 2). In a video that is viewed linearly without dropouts or backward jumps, the number of transitions from one section to the next would remain constant. However, this is rarely the case and because of these two factors transitions among sections can either decrease or increase.

In Fig. 56.4, we see two heatmap graphs depicting section transitions, one from the period before the assignment and the other from the period after the assignment and before the examination. In these heatmap graphs the lines correspond to the start sections, the columns to the destination sections and the numerical values are the number of transitions from the start sections to the destination sections. It is noticeable in Fig. 56.4a that besides the typical transitions from one section to the next (e.g., 90 transitions from section 1 to section 2), there are also transitions to other sections that stand out. Among these transitions, the ones to the previous sections are the ones that stand out clearly meaning that learners performed backward jumps probably because they wanted to view again a video segment before answering an assignment question.

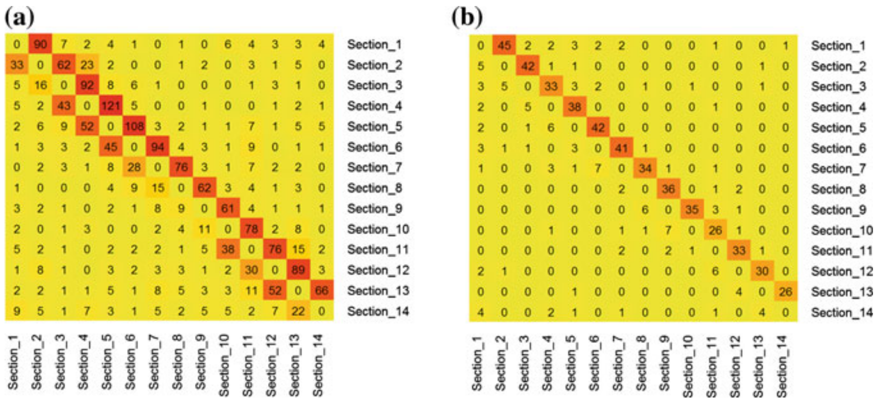

Fig. 56.4 Section transition matrix. **a** Transition matrix before assignment video visits 124. **b** Transition matrix after assignment video visits 61

When comparing the two images of Fig. 56.4, we can say that the 2nd transition matrix (Fig. 56.4b) is less “turbulent” than the 1st one (Fig. 56.4a), meaning that learners viewed videos in a more linear fashion. Moreover, we can say that although the table of contents was used for completing the assignment, students used it mainly to navigate to a previous section rather than making arbitrary jumps. The majority of the questions in the assignment followed the sequential order of the sections (e.g., a question related to section 2 was followed by a question related to section 3). However, some exceptions to the rule (but not all) can be distinguished in the graph. For example, there are 23 transitions from section 2 to 4 and 15 transitions from section 11 to 13. Both of these cases reflect exceptions in the sequence of questions.

Another aspect that was investigated was if video viewing yields better learning outcomes when accompanied by an assignment related to the video content. The number of students that enrolled for the course was much larger than the number of students that accessed the videos and these were mostly students that attended the lectures. The study that follows focuses only on the students that viewed the video lesson at least once and participated in the examination. Besides the overall examination mark, the student mark on the questions associated with the video (which counted for 50 %) was recorded and only this mark is used in the study conducted. This will be referred to as “video examination mark—VE mark.” In the investigation conducted, we tried to spot any effects that the assignment completion had in the VE mark.

We conducted an independent sample t test in order to check the effect of the assignment in the final VE mark. The sample of students was divided into two groups. The first group was comprised of 30 students who completed the assignment and the second group consisted of 27 students who did not complete the assignment. Findings from the t test indicate that significant differences ($p < 0.05$) exist in the mean scores of the two groups ($t = 3.289$, $p = 0.002$). Students who completed the assignment received higher grades (M = 6.63) in the VE mark than those who did not complete the assignment (M = 4.09). Hence, among the students that viewed the video, the ones that engaged further by attempting an assignment related to the video content achieved better in the examination.

According to the ICAP framework [1], there are 4 different levels of cognitive engagement while learning and there are differences in the learning outcomes depending on the engagement involved. The levels are the following: passive (simply receiving information), active (receiving information but at the same time doing something with the material), constructive (generating some information beyond the information presented in the material) and interactive (when students engage with each other through dialogue or collaborative activities). In our case, we have support that active engagement (watching a video and answering questions about the viewed material) is better than passive engagement (just watching the video).

56.5 Conclusions

The purpose of this paper was to present a video-based learning environment that aggregates video content with interactive elements and content that comes either from the educator or open Web resources. In the heart of the environment lies a module that records learner viewing behaviors and learner interactions with the aggregated elements. This activity data can then be analyzed with data analysis, data mining, and visualization techniques in order to understand learner viewing behaviors with respect to various parameters such as the elements integrated (e.g., quiz questions, table of contents), the type of videos used (e.g., instructional videos, documentaries, lectures), and the educational settings and learning scenarios in which the video learning activities take place. Some findings obtained from such analysis were presented in the paper. As future work we intend to incorporate more features into the environment (e.g., discussions), use the features within learning scenarios and conduct further data analysis and mining.

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Chapter 57
Investigating Determinants of Video-Based Learning Acceptance

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Abstract Online videos have been considered an instructional media for various pedagogic and training approaches, such as the flipped classroom and open online courses. Video-based learning (VBL) has gained prominence by extending the opportunities for education of all socioeconomic levels and by removing geographical boundaries and time constraints. Despite the great potential of VBL and its promising early outcomes, little is known about what influences individuals to adopt video technologies. Building on adoption acceptance theories and on empirical e-learning studies, we propose an adoption model for VBL consisting of five independent factors and one dependent (behavioral intention to adopt VBL) factor. A survey of 260 learners, who have used instructional videos in the past six months, was used to measure their behavioral intention to adopt VBL and what aspects enable or inhibit use. The five-predictor model accounts for 74 % of explained variance in students' intention to adopt VBL. In particular, results indicate that performance expectancy and computer self-efficacy have a positive effect on behavioral intention to adopt VBL. Additionally, effort expectancy and social influence positively impact performance expectancy, while computer self-efficacy is found to enhance effort expectancy and perceived behavioral control.

Keywords Video-based learning · e-learning · Podcasting · VBL · UTAUT · Intention · Technology acceptance · Adoption factors · Determinants

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57.1 Introduction and Background

The use of video for learning is becoming an increasingly important part of education. With the rapid growth of the Internet, video-based learning (VBL) has attracted the attention of educators worldwide. VBL is defined as *the learning process of acquiring defined knowledge, competence, and skills with the systematic assistance of video resources* [1]. In recent years, advanced video repository systems have seen enormous growth (e.g., Khan Academy, PBS Teachers, Moma's Modern Teachers) through social software tools and the possibilities to enhance videos on them. Most of the social software tools, including wikis, weblogs, Facebook, Twitter, MySpace, and e-portfolios, can potentially provide the means to promote VBL.

The introduction of VBL practices in education is not easy, and learners often hesitate to experiment with new instructional means. The success of each of the VBL tools and practices depends to a great extent on persuading learners to make use of the respective video materials. Although factors that contribute to the adoption of a system vary according to technology, some basic elements remain common. For instance, beliefs, social influences, and difficulties in routinizing technology in daily activities are some of the most widespread barriers for effective e-learning integration. Hence, it is important to examine VBL adoption through an integrative model, which will serve as a road map for future e-learning research.

In this light, an adoption intention model of VBL is presented and put to test in the following sections. The proposed model is grounded on ideas presented in the unified theory of acceptance and use of technology (UTAUT) [2], social cognitive theory (SCT) [3], and the theory of planned behavior (TPB) [4]. These factors are collected and associated through an extensive literature review of empirical studies of several e-learning tools [5–9], in order to produce a high predictive capability basis model for the research of VBL acceptance.

The rest of the paper is structured as follows. In the next section, we review the literature in the context of adoption of learning technologies and discuss the necessity to integrate the key factors associated with VBL. This is imperative in order to achieve higher predictive levels of learners' behavioral intention to adopt VBL. To this end, we propose a set of relationships which are molded into our proposed model. Section 57.3 includes a description of the constructs included in the model and their related elements. Section 57.4 presents the methodology and data used to test our research model, while Sect. 57.5 proceeds with the analysis and findings. In closing, Sect. 57.6 presents the conclusions and discusses several ideas for further research within this domain.

57.2 Background Theories

Several models and theories have been used to address the issues of different e-learning tools and to identify the cause and the effect of different factors in the adoption of e-learning tools. For instance, UTAUT [2], SCT [3], and TPB [4] are some of the most widely used models for examining intention to adopt a technological innovation at the individual level. The common ground of the models suggests that effort expectancy (EE), performance expectancy (PE), social influence (SI), computer self-efficacy (CSEF), and perceived behavioral control (PBC) are some of the most important aspects affecting learners' technology adoption.

In 2003, Venkatesh et al. [2] proposed the UTAUT model which integrates findings from a large number of previous technology acceptance model (TAM) [10] studies. In the UTAUT model, PE and EE are used to quantify the traditional constructs of perceived usefulness and perceived ease of use from the original TAM model. Even though UTAUT provides external variables that might affect PE and EE, and consequently the actual use of a system, these variables may not be the best fit for every system. Even in the context of e-learning, the variables that might influence the technology acceptance vary according to learners' needs and capabilities. However, effort expectancy, social influence, and performance expectancy influence the behavioral intention of the learner in many e-learning mediums, such as Blackboard [11] and Portals [12].

The SCT [3] posits that cognition exerts a considerable influence on the construction of one's reality, as it selectively encodes information, and imposes structure on actions [13]. This theory is used to explain how people acquire and maintain certain behavioral patterns, while it also provides the basis for intervention strategies [3]. Environment, people, and behavior are three factors that affect the evaluation of behavioral change. People learn through observing others' behaviors, attitudes, and outcomes. Compeau and Higgins [14] applied and extended SCT to the context of computer utilization, as such the first paper related to computer self-efficacy appeared in 1995. Nevertheless, the nature of the model and the underlying theory allow it to be extended to acceptance and use of information technology in general [2]. Even in the context of e-learning, Chang and Tang [15] found it to exert a significant influence of CSEF on learners' intention. Another widely used theory is the TPB proposed by Ajzen [4]. One of the most important variables in TPB is the individuals' perception of the ease with which the behavior can be performed (perceived behavioral control). Perceived behavioral control (PBC) has also been successfully applied to explain several issues concerning learners' intention to use technological tools [7]. A number of studies as presented in Table 57.1 have successfully adopted constructs from UTAUT, SCT, and TPB to explain the acceptance of e-learning technologies. While each of these researches (Table 57.1) examined several interesting issues, they do not use an integrative model of relationships for the context of e-learning requirements.

Table 57.1 Constructs and relationships

Factor	Relationships	Supporting literature
EE	EE → PE	Ngai et al. [6]; Lee et al. [16]
	EE → BI	Sanchez-Franco [9]
PE	PE → BI	Maldonado et al. [12]; Chang and Tang [15]
SI	SI → BI	Lee and Lin [8]; Miller et al. [17]
	SI → PE	Lee and Lin [8]
CSEF	CSEF → BI	Chang and Tang [15]; Bilquis and Yair [18]
	CSEF → EE	Gong et al. [5]; Sánchez and Huero [19]
	CSEF → PBC	Deduced from SCT; Gong et al. [5]; Shih [7]
PBC	PBC → BI	Shih [7]; Chau and Hu [20]

57.3 Conceptual Model

The UTAUT, SCT, and TPB models have been applied to study adoption of technological innovations for several e-learning tools, including Blackboard [11], Podcasting [8], Moodle [20], Portals [12, 15], and others. As a result, most of their constructs have been tested and validated several times in a range of contexts, with behavioral intention being used as the dependent variable. As aforementioned, the main antecedents of BI include EE, PE, SI, CSEF, and PBC. The proposed relationships as shown in Fig. 57.1 are drawn from the prior literature and are adapted to the VBL context.

Computer Self-Efficacy: Self-efficacy beliefs determine how people feel, think, motivate themselves, and behave [3]. Computer self-efficacy measures how an individual rates his/her capability to use a computer [14]. Based on the previous studies [5, 15, 18], CSEF is found to be related to learners' BI and PBC to use an e-learning tool. Hence, we integrate this factor and its connections into the general framework of the proposed intention adoption model of VBL.

Effort Expectancy: Effort expectancy is conceived as the degree of ease associated with the use of the particular system. In our research, EE refers to the degree to which studying by using an e-learning tool is free of effort. Also, Ngai et al. [6] and Lee et al. [16] indicate that EE was positively associated with PE and BI in the e-learning context. Thus, in our model, we propose that these relationships will stand in a VBL context.

Performance Expectancy: Performance expectancy refers to the degree to which learners believe that e-learning improves their academic performance. A number of researches have already empirically supported the effect of PE on learners' BI (e.g., [6, 12, 15]). Hence, in terms of VBL, it is reasonable to include PE into our proposed model.

Social Influence: Social influence is defined as the degree to which the learner perceives that others approve his or her action of using an e-learning tool. Community identification was defined as the association with a learning community. Hars and Ou [21] confirmed that a user's identification with a community

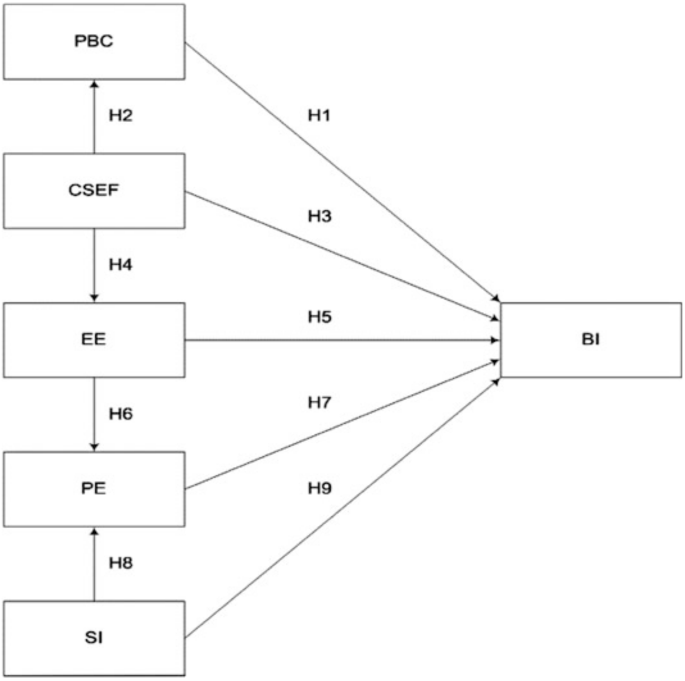

Fig. 57.1 The conceptual research model

played an important role in his or her intentions. Furthermore, some researches [8, 17] indicate the positive effect of SI on learner PE and BI. Hence, we tend to include SI into our proposed model as a critical construct.

Perceived Behavioral Control: Perceived behavioral control refers to a person's potential to perform the behavior in question, i.e., how easy or hard the behavior is perceived to be [4]. This study therefore considers PBC as individual perceptions of their control over the e-learning tool. Prior studies [7, 20] suggest that PBC is a strong predictor of BI to use e-learning tools; as such, it is rational to include and test PBC into the proposed VBL adoption model.

57.4 Measurements

Our research methodology was based on individual responses collected through a custom-built questionnaire. The survey is comprised of two main parts: The first included questions on demographics (gender, education, marital status, age), while the second asked respondents to evaluate personal attitudes and perceptions in accordance with the constructs defined previously. Questionnaires were distributed in various locations (universities, public areas) and e-mails with digital

Table 57.2 Sample demographics

Demographic profile		(%)
Gender	Male	49.6
	Female	50.4
Marital status	Single	85.4
	Married	14.6
Age	15–20	16.3
	21–25	36.2
	26–30	24.4
	31–35	13.8
	36+	9.3
Education	High school	8.9
	University	46.3
	Postgraduate	44.7

questionnaires sent to a number of mailing lists of individuals who had partaken in educational activities through VBL. The survey was open during a 2-month period (October–November). The final sample of respondents is comprised of 260 learners who had experienced VBL in the last six months. Table 57.2 depicts the detailed demographics of our sample.

The constructs used in this research were evaluated in terms of reliability and validity. Reliability was tested with the use of the Cronbach alpha indicator, which required all constructs to have values greater than 0.7. Validation analysis consists of convergent and discriminant validity. Establishing validity requires that average variance extracted (AVE) is greater than 0.50 and the correlation between the different variables in the confirmatory models does not exceed 0.8 points as this suggests low discrimination and that the square root of each factor's AVE is larger than its correlations with other factors.

Goodness of fit (GoF) describes how well the model fits its data. Here, several fit indices were used to assess model data. The values of root mean square error of approximation (RMSEA), comparative fit index (CFI), normed fit index TLI, and x^2/df ratio were all used to evaluate model data fit. RMSEA less than 0.05 suggests good model data fit; between 0.05 and 0.08, it suggests reasonable model data fit, and between 0.08 and 0.1, it suggests acceptable model data fit. CFI and TLI indices greater than 0.90 suggest good model data fit and those greater than 0.80 suggest adequate model data fit. A x^2/df ratio less than 3 is acceptable.

57.5 Findings

First, an analysis of reliability and validity was carried out. Reliability testing, based on the Cronbach alpha indicator, shows acceptable indices of internal consistency since all constructs exceed the cutoff threshold of 0.70. The AVE for all constructs

Table 57.3 Descriptive statistics and correlations of latent variables

Construct	Mean (SD)	CR	AVE	CSEF	EE	PE	SI	PBC	BI
CSEF	4.19 (1.36)	0.711	0.586	**0.765**					
EE	5.44 (1.02)	0.803	0.626	0.125	**0.791**				
PE	5.36 (1.22)	0.938	0.688	0.108	0.335	**0.829**			
SI	4.16 (1.53)	0.822	0.712	0.134	0.163	0.354	**0.844**		
PBC	5.81 (1.15)	0.808	0.668	0.134	0.427	0.312	0.103	**0.818**	
BI	5.75 (1.25)	0.919	0.658	0.129	0.383	0.639	0.337	0.318	**0.711**

Note Diagonal elements (in bold) are the square root of the average variance extracted (AVE). Off-diagonal elements are the correlations among constructs (all correlations are significant, $p < 0.01$). For discriminant validity, diagonal elements should be larger than off-diagonal elements. *CSEF* computer self-efficacy; *EE* effort expectancy; *PE* performance expectancy; *SI* social influence; *PBC* perceived behavioral control; *BI* behavioral intention

ranges between 0.586 and 0.712, exceeding the cutoff threshold of 0.50. Finally, all correlations are lower than 0.80, and square root of AVEs for all constructs is larger than their correlations. Findings are illustrated in Table 57.3.

The fit indices of the research model are within the recommended range. Specifically, χ^2/df = 2.69, TLI = 0.913, CFI = 0.928, and RMSEA = 0.08. The estimated path coefficients of the structural model were examined in order to evaluate our hypotheses. Figure 57.2 presents the analysis of the research model.

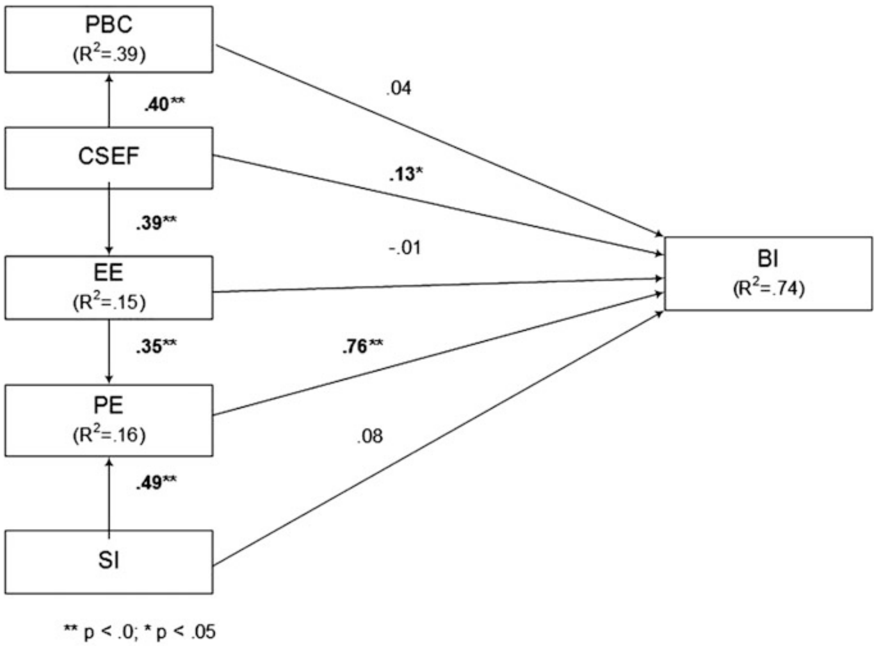

Fig. 57.2 SEM analysis of the research model

Computer self-efficacy has a positive effect on effort expectancy, perceived behavioral control, and behavioral intention, supporting hypotheses H2–H4. However, the effect of perceived behavioral control on behavioral intention was found to be non-significant, rejecting H1. Furthermore, effort expectancy has a positive effect on performance expectancy, supporting H6, but has no significant effect on behavioral intention, rejecting H5. In addition, performance expectancy has a positive effect on behavioral intention, supporting H7. Regarding social influence, we found that it has a significant effect on performance expectancy but has none effect on behavioral intention. The findings support H8 but reject H9. Finally, multiple correlations (R^2) are presented in Fig. 57.2 as well. The R^2 for effort expectancy was 0.15, for performance expectancy was 0.16, for perceived behavioral control 0.39, and for behavioral intention was 0.74.

57.6 Discussion and Conclusions

Our research contributes to existing literature by proposing and testing a conceptual model for VBL acceptance; the model is based on the related work of e-learning tools' adoption. The proposed five-predictor model integrates various e-learning theories and accounts for 74 % of explained variance in students' intention to adopt VBL.

This research differentiates from previous studies by collecting and integrating several key variables in a unified model for VBL acceptance. It is likely to be a useful conceptual framework for future research design in the area of VBL. Beyond the conceptual model development, we empirically measured learners' VBL adoption.

We want to emphasize that our findings are clearly preliminary with certain limitations. Future research should concentrate on further refinement of the proposed conceptual model by applying and evaluating it on focused categories of learners (e.g., MOOC learners, flipped classroom). Furthermore, there is room to include additional contextual factors. This will enable the identification of more precise conclusions and facilitate the investigation of VBL determinants more accurately. Thus, this study can serve as a spark for other scholars and practitioners to further examine factors affecting VBL adoption.

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Chapter 58
Visualization Improvement in Learning Analytics Using Semantic Enrichment

Gloria Fernández and Olga Mariño

Abstract This chapter presents a learning analytics and knowledge representation framework to support analysis and visualization of data extracted from MOOC (Massive Open Online Course). Data analytics provides methods and tools to analyze big data sets. In the context of learning, these methods have helped analyze MOOC data, mainly to characterize groups of learners. On the other hand, semantic Web and eLearning research groups are working on ontological representation of learning scenario components. Our project joins those efforts, both to discover relations through bottom-up analytics and to organize and focus the analysis with a semantic representation of the learning scenario. The first section states the problem and sketches the solution. The proposed framework is composed of four stages: data cleaning and formatting, bottom-up data analysis, semantic analysis, and finally visualization. The specification and implementation of each step is described in the following sections. The last section presents the evaluation of the project and conclusions.

Keywords Learning analytics · Ontology · Semantic representation · MapReduce and visualization

58.1 Introduction

Massive open online courses (MOOCs) are offering new opportunities as well as new challenges for technology-enhanced learning. Its unique feature of having hundreds or thousands of students enrolled in a course and whose interactions in the

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platform are recorded, offers the opportunity to analyze educational big data, and states the social challenge of using these analyses to enhance the quality of eLearning and to improve the student learning experience. To address this challenge, researches have been conducted in the area of educational big data analysis, known as learning analytics (hereafter LA). And, as we will present in this chapter, learning analytics can be enriched, by using the course pedagogical structure or learning design as a top-down structure of activities, material, evaluations, and other course events.

MOOCs are learning management systems that gather hundreds of students [1], they are taught by experts, are free and are delivered online. There are two different kinds of MOOC, xMOOC, which have the structure of a traditional classroom course with resources that support the class and cMOOC oriented to connectivism that encourage students to use tools and applications to promote learning by establishing connections.

MOOCs data collection starts in May 2012 [2] with the first MIT MOOC. 155,000 students were enrolled and the course provider collected a data set of 110 GB. Following courses collected even larger data sets. Since then, researchers have worked analyzing these data to identify patterns and behaviors within the scope of *Learning Analytics*.

Researchers on LA are mostly focused on profile identification [3–5] with the main purpose of establishing relations between student profiles and student desertion [6], which is the principal problem detected in the MOOC phenomenon [7]. Most LA processes are focused on xMOOC, which account for the vast majority of current MOOC. Those studies do not take into account the pedagogical and course structure and their relationship between them and the student desertion [8].

This project is focused on xMOOCs. Most xMOOCs learning design is a linear workflow, corresponding to the course syllabus. The course is divided into sequential modules, which in turn can be further divided. Final activities are mainly video watching, eventually text reading, and multiple-choice close question evaluations or productions.

For this project, the preceding interactions will be analyzed using learning analytics techniques enriched with a knowledge engineering layer, in which the course learning design is described in terms of a domain ontology. Analysis data will be displayed with the integration of visualization tools.

The courses that are analyzed have a specific format that consists of 7–8 videos, containing 1–2 in video quiz questions each, 3 or 4 quizzes, and 1 assignments per module. One of the courses has also peer-evaluated challenges and a final exam.

The previous description corresponds to courses from the Stanford Open-EdX project. Data sets of two courses were provided by Stanford Vice Provost for Teaching and Learning (VPTL)[1] Researcher Data Account Request. Each data set consists of three basic tables with video, activity grade, and events information.

[1] http://vpol.stanford.edu/research.

The framework of this project consists of four stages: The first one is the data set generation, the second one is the knowledge engineering process, the third one is the learning analytics process, and the last one is the visualization. This chapter presents one possible implementation of the framework. The implementation uses MapReduce programming model to process information, MongoDB to store information as documents, R programming to analyze data, shiny-server to visualize, and finally describes a knowledge engineering process using OWL and RDF to enrich the analytics and represent the learning scenario knowledge.

58.2 Context

Big data concept is defined as the handling of huge amounts of information (volume). However, big data involves two additional attributes related to variety (structured data, semi-structured data, and non-structured data) and velocity (processing real-time data). This definition is known as the three Vs definition [8] (3Vs). Big data incorporate interesting challenges to the scientific community. One of these challenges, with great relevance for this project, corresponds to analytics in big data [9] that allow to query and analyze big data using advanced statistics and analytical techniques, so that it can be possible to understand the data, to discover information and to conclude relevant aspects from these data so as to improve decision making.

On the other hand, the boom of Internet, the hardware capacity worldwide (connection, infrastructure, etc.), and the improvement of its infrastructure of those capacities and communication in a general way [10] have unleashed a important phenomenon that consists of online courses that gather a significant number of students, experts, didactic tools, and many other elements that facilitate the online learning context, and the tendency described is known as MOOCs [4].

At the crossroad of these domains: big data analytics and MOOCs is the area of Learning Analytics. Although the term Learning Analytics is relatively new, it is worth mentioning that the research in this area has started earlier with different names. Ryan S.J.D. Baker and KalinaYacef presents, in the second annual international conference on Educational Data Mining, EDM2009 held in 2009 [5], a state of the art review in the field of Educational Data Mining (EDM). Bakers and Yacef revision shows that Learning Analytics starts as EDM, which uses methods for Data mining, statistics and visualization, and web mining (clustering, classification, mining patterns, text mining). In 2005 those techniques where sheltered under the term Learning Analytics (LA), defined by the solar project [12] as follows: "Learning Analytics is the measurement, collection, analysis and reporting of data on learning and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs."

This chapter focused on learning analytics in MOOC courses. Main focus is on student profiling [4] that proposes a student's classification based on the students' interaction within the course; this classification identifies student in four groups;

viewers, solvers, all-rounders, and collectors. Other important study presents a different classification [5] which is based on the students' interaction with videos and assessments in different courses, and this chapter presents four groups: on-track, behind, auditing, and out.

The project presented in this chapter consists of a framework for analyzing big data sets from xMOOC courses, implemented in Stanford Open-EdX platform. Two courses delivered by Stanford University were analyzed; the first one was used to build the framework and the second one to test it. As MOOCs in the EdX platform follow a common macrostructure, modification of the proposed framework accounts for the data set of other EdX courses should be straightforward.

The principal contribution of this chapter is the incorporation of knowledge engineering to represent elements using ontologies to enrich the learning analytics process in xMOOC courses.

58.3 Design and Implementation

This section describes the different software and hardware elements that this project uses to implement semantic enrichment in learning analytics. As it was mentioned before, the project consists of four stages; the next three points explain each of those stages, and at the end of the section, an architectural proposal is presented.

58.3.1 Data Set Generation and Data Storage

Original information from Open EdX consists of three files stored in .cvs format; those files present information about activity grades, event information, and video interaction of each student. The course selected to build the framework was "SciWrite in the Science," in a session delivered to 15,092 students.

The information of the course is stored in a column–row format, providing different inputs for one student in each file. For example, one student has different records for every activity that he/she made within the course, as well as different records in the video interaction and events files. As the main unit of analysis of the project is the student, a first process of student records integration was designed and implemented.

In the design process, three types of records per student were identified: one for the activity grades, one for the events, and one for the video interactions. Students' data were store in the NoSQL database MongoDB. MongoDB stores documents, so in the project each document represents one student. As MongoDB works with JSON files, arrays were used to store each type of information for a student: the activity grades, the events, and the video interactions, which mean that every document has three arrays with all the information of a particular student.

The reorganization of the original files into JSON files and their storage in MongoDB documents were achieved using a Hadoop cluster (5 machines) and a MapReduce pattern called “structural to hierarchical.”

58.3.2 Learning Analytics Process

The principal goal of this stage is to identify the student’s behavior within a course and in a general way to show some specific statistics of the course. As the course was divided into eight (8) different modules, each of them was analyzed separately. Through this analysis, it was possible to identify the student’s profile, as described by [4, 5]. For example, the on-track students are identifiable from the second week of the course and they remain steady during the whole course.

To implement this stage of the framework, the project uses the R programming language. R provides for the statistical analysis of big data. As the input of this stage was MongoDB documents, a preprocessing was needed to make those documents readable by R. These preprocessing was implemented with R extended “rmongodb” package, an extended functionality of R, which allows the R language to access MongoDB documents and their structure.

58.3.3 Visualization

To plot the analytics information, R offers different visualization packages, which recover and display R accessible data and statistics. For the implementation of the project, the following packages were used: rCharts, reshape, ggplot2, and googleVis. Integration of other packages is straightforward at this stage, as data are cleaned and readable by R.

As the project expects to implement some “flexible” analytics, that is, to ask different questions without changing any code, a tool to provide for the interaction with visual data was needed. For this implementation, we selected Shiny. This Web application server offers interactive graphics through the use of reactive functions and widgets. Figure 58.1 shows some interactive widgets that were used in the project.

It is worth noticing that to plot the stored information, some data manipulation and modification was needed, as each Shiny package imposes particular constraints in the format it is able to handle—for example, some packages require a particular columns to be of a particular type, for instance character or numeric.

The developed scripts for these data transformation should be useful for other EdX courses as well.

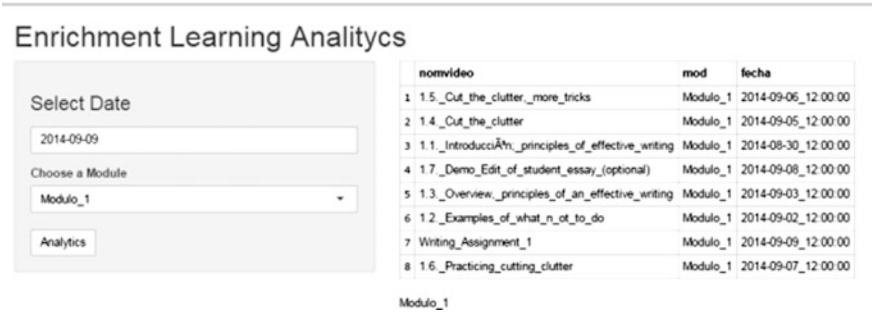


Fig. 58.1 Shiny server reactive widgets

58.3.4 Knowledge Engineering

One main contribution of this project was to enrich the learning analytics with semantic information of the course. The idea behind this semantic enrichment is to do better analytics of the data by informing the analysis process of important semantic notions and relations. In the case of MOOCs this knowledge layer could, for instance, tell to the analytics process that a video is preceded by another one, that a video is required to present a quiz or to send an assignment, or that a set of resources are all inputs of a particular activity.

This section explains this semantic layer of the project and its integration of this layer with the preceding stages of analytics.

In the context of TEL (technology-enhanced learning), there has been some research works to enrich data semantically. For example, [13] presents an ontological framework to contextualize learning virtual objects. This approach establishes a connection between the learning environment and the context.

As in the previous example, our research searches to establish a relationship between the pedagogical structure of the course (the course workflow), the student behavior, and the student's desertion, to identify patterns to guide decision making.

To achieve this goal, the project integrated a knowledge representation layer. The knowledge represented in this layer was extracted top-down from the course description, not from the interaction data. Knowledge was represented in the form of a domain ontology. An ontology can be described as a shared conceptualization of a domain knowledge. Its constituting elements are classes, relations, and properties as well as constraints, instances, and assertions. In this case, the domain represented is instructional design and the classes described in the ontology are the concepts related to both the learning workflow (such as module and activity) and the resources provided for the different activities (such as video and quiz). Relations include a resource being tied to a particular activity while properties include the scheduled time for the execution of a particular activity in the particular session of the course. Each video, quiz, activity, production, and module of the particular MOOC was integrated in the ontology as an instance related to the corresponding concept.

The ontology was built in RDF/XML format using the Protégé ontology editor. The connection between the ontology and the date consists of two phases. In a first phase, the ontology is queried using the ontological query language SPARQL. Queries in SPARQL may refer to any element in the ontology. Again, although the developed queries are particular to the course used to build the framework, as the ontology TBox (classes, relations, and properties) are common to most EdX courses, they should be easily adapted to other courses.

A SPARQL query retrieves a set of ontology elements. In the second phase, these elements are used to filter the MondoDB database, thus reducing the amount of information to the one that is more pertinent for the domain. This information will then be processed in the analytics process. Using the interactive Shiny application, the user can select information such as activities from a specific module, or activities that should be achieved before a specific date and so on. The integration of these phases was made through a Fuseki-Jena endpoint setup to allow Shiny to query the RDF ontology, to filter data in Mongo, and to display the visualization.

58.4 Tests

The framework and its implementation were tested with two different courses: "SciWrite" and "How to Learn Math," the tool displays graphs like the one presented in Fig. 58.2.

"SciWrite" was used to build the framework and has 15,105 students, the data set size was about 16 GB, and it was issued in September 2014. On the other hand, the course

	infoMOD1$resource_name	V1
1	Session 1, part 1	286099
2	Session 1, part 2	211921
3	Session 1, part 3	223380
4	Session 1, part 4	569341
5	Session 1, part 5	166199
6	Session 1, part 6	115211
7	Session 1, part 7	126577
8	Session 1, part 8	100690

	nomvideo	mod	fecha
1	Session_1._part_7	Modulo_1	2013-06-21_12:00:00
2	Session_1._part_2	Modulo_1	2013-06-18_12:00:00
3	The_Situation._part_1	Modulo_1	2013-06-15_12:00:00
4	Session_1._part_5	Modulo_1	2013-06-20_12:00:00
5	Session_1._part_8	Modulo_1	2013-06-22_12:00:00
6	Session_1._part_3	Modulo_1	2013-06-18_12:00:00
7	Session_1._part_6	Modulo_1	2013-06-20_12:00:00
8	Session_1._part_1	Modulo_1	2013-06-17_12:00:00
9	Session_1._part_4	Modulo_1	2013-06-19_12:00:00

Fig. 58.2 Implementation results

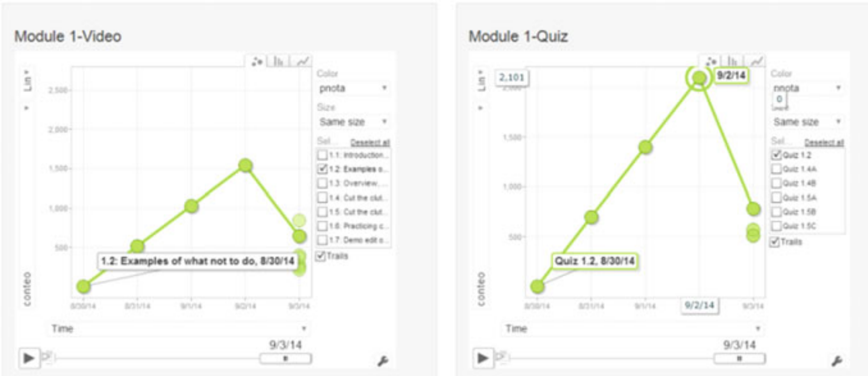


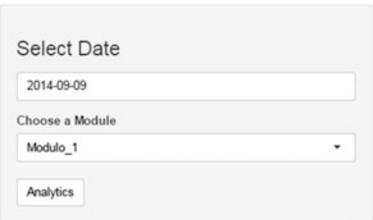
Fig. 58.3 Module 1. Video and quiz analyze

"How to Learn Math" was used to make some tests of the framework. This course was offered in 2013, it had 18.000 students registered and produced a 15GB dataset.

As mentioned before, the date were analyzed by course modules. This section presents information of the first module. Figure 58.3 represents video and quiz analytics. It shows the number of students accessing a specific resource (video or quiz) in a specific date. This view also queriesthe ontology to relate dates and resources to course activities, helping the user (teacher, MOOC designer or student) understand the peaks indelivery dates of each resource. For example, it could be possible to identify why there was a peak on September 2nd or why there was poor activity during the next days. It could be possible to query the expected days in which students should perform the activity. While doing so, we found that student's behavior is similar in each module, they use to perform activities one day before the deadline.

It is important to explain that video and quizzes in MOOC courses have not a strict deadline, and students can access these resources any time. Because of that this project considers a tentative date in which students performed a specific activity; this date depends on the time expected for students to send their assignment, because assignments do have a deadline.

The left side of Fig. 58.4 represents the filter that is used to query OWL ontology to identify some precedence information as well as to query instances from a



	nomvideo	mod	fecha
1	1.5._Cut_the_clutter,_more_tricks	Modulo_1	2014-09-06_12:00:00
2	1.4._Cut_the_clutter	Modulo_1	2014-09-05_12:00:00
3	1.1._IntroducciÃ³n:_principles_of_effective_writing	Modulo_1	2014-08-30_12:00:00
4	1.7._Demo_Edit_of_student_essay_(optional)	Modulo_1	2014-09-08_12:00:00
5	1.3._Overview,_principles_of_an_effective_writing	Modulo_1	2014-09-03_12:00:00
6	1.2._Examples_of_what_n_ot_to_do	Modulo_1	2014-09-02_12:00:00
7	Writing_Assignment_1	Modulo_1	2014-09-09_12:00:00
8	1.6._Practicing_cutting_clutter	Modulo_1	2014-09-07_12:00:00

Fig. 58.4 Learning analytics filter

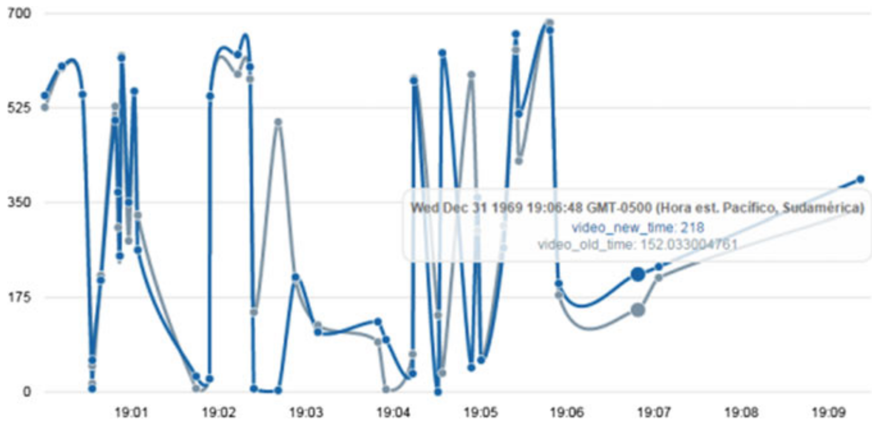


Fig. 58.5 Video analysis

specific module and the right side represents the elements retrieve from the ontology after click on analytics button to apply the filter and query Mongo.

58.5 Results

Video information was very challenging to analyze because at first it was not clear what to ask about it. Because of that understanding the data was tough until it identifies the specific activities a student could perform with the video. A particular interaction traced in the video-watching activity was called seek_video. This event was stored when a student moves the playing position of a video, seeking a particular segment of the video. When analyzing seek_video interaction, it was interesting to identify how is the students' interaction in a single video so that it could be possible to focus on those parts of video that students are looking into a video or identify which parts are not being watching by a student. For example, Fig. 58.5 shows how this information is displayed using Shiny; it represents on the x-axis the moment in time in which the student performed the action "seek" a specific video and the y-axis indicates the time interval, also in seconds, that the student skipped forward or backwards in this video.

58.6 Conclusions and Further Work

In an analytic process, questions are the most important aspect, not only because asking the wrong question leads to useless information but because they define the scope of the project and they guide the selection of both the tools to perform the different stages of the analysis and the visualization tools to be integrated to the user dashboard. The integration of the ontological semantic layer helps both to focus the project on pertinent questions and to take advantage of the analytics provided so as to reduce the gap between this analytics and the decision taking that follows.

At the beginning, the project intended to compare two different types of MOOCs, classical MOOCs or xMOOCs, as the courses that were described in this document and cMOOC (connective) to compare the performance and behavior in each of these types of courses. However, it was not possible to collect information or find a data set from any cMOOC. We strongly recommend to extend this framework to that kind of courses. One such course which data might be interesting to analyze is "LINK5.10x Data, Analytics, and Learning," also on the EdX platform.

Video analysis is a very interesting topic in learning analytics. The analysis of video interaction should be enriched with information regarding its content and relations between this content and the goals of the module or the module homework. Metadata related to both the module and its resources could be a starting point in this direction.

Learning analytics is focused on past information, data sets analyzed on batch. A promising line of research in this domain is real-time analytics, which could integrate in the analysis past session data sets as well as current session generated data sets so as to inform the decision maker on particular current issues that could be enhanced to give a better learning experience to current student, not only to following groups. To apply this solution in a real-time analytical project, it is necessary to redefine the architecture so that process and storage could be better supported.

Finally, a very active research line concerns adaptation and personalization. Real-time analytics and semantic referencing of both resources, activities and students, could allow for personalization and adaptation of MOOC, as proposed by [14].

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