Lecture Notes in Educational Technology

Fan Yang
Zhenghong Dong

Learning Path Construction in e-Learning

What to Learn, How to Learn, and How to Improve

Springer

Lecture Notes in Educational Technology

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ISSN 2196-4963 ISSN 2196-4971 (electronic)
Lecture Notes in Educational Technology
ISBN 978-981-10-1943-2 ISBN 978-981-10-1944-9 (eBook)
DOI 10.1007/978-981-10-1944-9

Library of Congress Control Number: 2016945965

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer Science+Business Media Singapore Pte Ltd.

Preface

Whether in traditional or e-learning, it is important to consider what to learn, how to learn, and how well students have learned. Since there are various types of students with different learning preferences, learning styles, and learning abilities, it is not easy to provide the best learning approach for a specific student. Designing learning contents for different students is very time-consuming and tedious for teachers. No matter how the learning process is carried out, both teachers and students must be satisfied with students' learning performance.

Therefore, it is important to provide helpful teaching and learning guidance for teachers and students. In order to achieve this, we proposed a fine-grained outcome-based learning path model, which allows teachers to explicitly formulate learning activities as the learning units of a learning path. This allows teachers to formulate the assessment criteria related to the subject-specific knowledge and skills as well as generic skills, so that the pedagogy could be defined and properly incorporated. Apart from defining the pedagogical approaches, we also need to provide tailored learning contents of the courses, so that different types of students can better learn the knowledge according to their own learning abilities, knowledge backgrounds, etc. On the other hand, those learning contents should be well structured, so that students can understand them. To achieve this, we have proposed a learning path generation method based on Association Link Network to automatically identify the relationships among different Web resources. This method makes use of the Web resources that can be freely obtained from the Web to form well-structured learning resources with proper sequences for delivery. Although the learning path defines what to learn and how to learn, we still needed to monitor student learning progress in order to determine proper learning contents and learning activities in an e-learning system. To address the problem, we proposed the use of student progress indicators based on Fuzzy Cognitive Map to analyze both performance and non-performance attributes and their causal relationships. The aim is to help teachers to improve their teaching approaches and help students to reflect their strengths and weaknesses in learning. This monograph focuses on the intelligent tutoring e-learning system, which provides an intelligent approach to design and delivery learning activities in a learning path. Many experiments and comparative studies on both teachers and students have been carried out in order to evaluate the research of this monograph. The results show that our research can effectively help teachers to generate high-quality learning paths, help students to improve their learning performance, and offer both teachers and students a better understanding on student learning progress.

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Chapter 1
Introduction

1.1 Overview

E-Learning can provide various technological support to assist teaching and learning. This technological support mainly includes developing learning contents to instruct learning, setting up learning environments to engage learning, designing platforms and tools to enhance learning, organizing and standardizing learning resources to make the learning contents reusable and more formal. Constructing learning path is to organize a set of Units of Learning (UoL, which is the smallest unit providing learning events for learners, satisfying one or more learning objectives [Gome09]) in sequence and to plan how student learning will happen, which is actually a critical topic in designing platforms and tools. Because a learning path contains the information about what to learn and how to learn, it can help teachers to manage student learning and help students to improve their learning efficiency. There are different types of E-Learning systems, including the traditional e-learning system, adaptive E-Learning system, instructional design system, intelligent tutoring system, and service-oriented e-learning system. They are used to focus on long-distance E-Learning system, but now they focus on different aspects of the E-Learning systems by providing adaptive teaching approaches and feedbacks, consistent and reliable learning materials, curriculum sequencing mechanisms, and Web services, respectively. More details about these E-Learning systems are given in Sect. 2.2.2. Our monograph provides an intelligent service to design the learning activities and to arrange the learning path, so that it can be applied to intelligent tutoring system. Learning path construction (or curriculum sequencing) organizes a series of learning activities that are disseminated with proper teaching approaches to build up student knowledge. As defined in the work of [Brus92], Intelligent Tutoring System relies on curriculum sequencing mechanisms to provide students with a learning path through learning materials. This research on learning path construction is one of the major work in Intelligent

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_1

Tutoring System. Existing methods [Chen08, Farr04, Limo09, Yang05] formulate learning paths based on knowledge elements. While this allows the E-Learning systems to work out and organize suitable instructional contents based on the knowledge elements, such as the difficulty levels and the topic categories of the knowledge elements. However, such a formulation is not comprehensive enough.

The main concerns of various studies on learning path construction include how to generate the learning contents for each UoL, how to design the UoL to support different forms of learning activities, and how to identify the relationships among UoLs and delivery them in sequence. Our monograph focuses on providing an intelligent tutoring system to construct learning path which can pedagogically design teaching strategies based on learning outcomes, generates learning resources adaptive to different students, and analyses student learning progress in terms of their performance related attributes as well as non-performance related attributes. During the learning process of each UoL, we need to monitor student learning progress and evaluate student learning performance, so that we will be able to construct the best learning paths for different types of students according to their learning abilities and preferences, etc.

1.2 Motivation

This section discusses about why the work on learning path construction is valuable. The advance in the Internet and mobile technologies significantly improves the accessibility of the Web to nearly anytime and anywhere. Together with the emerging Web standards, such as HTML5, CSS3 and WebGL, the Web has become a popular platform for developing applications. Particularly, E-Learning is considered as one of the potentiality killer-applications, and comprehensive learning platforms can be easily developed by exploiting learning resources available on the Web.

The Web provides a shared workspace for students to interact and learn through cooperation, while different forms of Web-based communication technologies allow individual students to learn at their own pace [Li08]. Normally, it is not easy for a student to manage the student's study on the student's own because of lacking self-control, limited individual learning experience, especially when the students know nothing about the course. Even if students would like to learn, they are still confused with what to learn at first and then next and not sure what they can achieve. We need a method to make students know clearly not only what to learn, but also how to learn and how to improve.

Internet also provides a lot of useful Web resources that can be freely obtained from authenticated Websites, such as Wikipedia, BBC, Reuters, etc., where the contents, quality and presentation styles can be guaranteed and suitable for learning. If these Web resources can be converted to well-structured learning resources which have relationships in between and contain attributes as the criteria to select suitable learning resources, then we can automatically generate the knowledge structure on the basis of the learning resources. The knowledge structure builds up the relationships of the knowledge concepts as well as the relationships of learning resources.

During the learning process guided by the learning path, students are making progress to obtain more knowledge as well as improving their learning abilities. It is necessary to monitor what they have achieved and analyze which factors would affect their learning progress, so that they can provide the information to further manage their learning. However, it is not easy for a teacher to design learning activities for different students, especially there are too many factors that may affect their learning qualities. Monitoring student learning progress help us to analyze how an attribute affects a student's learning performance on another attribute. Students can understand their own learning performance and how to improve. On the other hand, teachers can adjust their teaching approaches. Both parties can identify main parameters that affect student learning progress and their developments in different attributes.

1.3 Related Work

A learning path is the implementation of a curriculum design. It comprises elements forming steps for students to go through for acquiring knowledge and skills. In existing work, learning outcome assessment is generally tied up with these steps. The discussion includes conventional classroom teaching, learning path generation systems and de facto standards that define learning paths.

Analyzing student learning progress is not trivial. Different subjects (or learning activities (LAs) [Yang10]) have different assessment criteria, where some are subject specific but some are shared among subjects. On the other hand, student learning styles and learning modes also play significant roles on how a student perform and make development in different assessment criteria. We have developed the student attribute descriptors to provide a more complete picture on student learning progress and development.

1.3.1 Student Attributes

To model student learning state, subject specific and general attributes can be considered. By considering subject specific attributes [Chen05], evaluates how students make progress on their understanding of certain learning materials. The method runs maximum likelihood estimation on the level of understanding claimed by students against the difficulty of learning materials. Mitrovic [Mitr01] investigates self-assessment skills of students by identifying the reasons for a student to give up solving a problem and the ability of the student to identify the types of problems to work on. The method collects student learning progress based on mainly two attributes: the difficulty level and the type of problem. Guzman et al. [Guzm07] studies the use of self-assessment tests to improve student's examination performance; the tests generate questions adaptively based on student's answers to each previous question. The method applies item response theory (IRT) to predict student's probability of correctly answering questions based on a student's knowledge level. A student is assessed based on the correctness of the answers and the probability distribution of these corrected answers on each knowledge level, i.e., the probability of the corresponding knowledge level, associated with each concept.

Besides subject specific attributes, there are also non-subject related attributes governing student learning progress, which are referred to general attributes. Yang and Tsai [Yang10B] studies how students learn through peer assessment. Students are asked to qualitatively assess peers based on feasibility, creativity and knowledge, where the first two are general attributes, which respectively represent the ability to identify appropriate learning materials and to come up with original ideas. Gresham et al. [Gres10] investigates the minimal set of social behavior to be included in the brief behavior rating scale (BBRS), forming a compact progress monitoring tool for efficiently identifying the change in student's social behavior. Limongelli et al. [Limo09] shows that learning styles are critical to student learning and can help to identify adaptive learning materials for students. In addition, learning styles can be evolved over time. As shown above, existing works model student learning state using a few specific types and numbers of attributes. They give students feedback on certain aspects but can hardly provide students a global picture showing how improvement can be made across different subjects or learning activities, as they do not consider that student learning progress can be governed by student learning performance and development in both subject specific and general attributes as well as the causal relationships among such attributes.

1.3.2 Student Assessment

To evaluate student learning progress, existing work has developed ways to collectively model knowledge and skill sets of students. For instance [Chen01], uses attributed concept maps to represent both knowledge gained by a student after a learning activity and the teacher's prototypical knowledge. A fuzzy map matching process is then used to compare both maps to determine how well the student has progressed in the learning. Feng et al. [Feng09] proposes to use a fine-grained skill model to represent a set of skills hierarchically. A generalized linear mixed effects model is then applied to generate statistic information to describe the student progress on different skills. Stecker et al. [Stec05] proposes curriculum-based measurements to intuitively monitor student progress. It monitors student knowledge and skills frequently and depicts the results graphically in order to show what progress a student has made globally over a period of time and locally among each piece of knowledge/skill, and whether such progress meets the teacher expectation. Reference [Bake10] predicts student performance use the contextual estimation of student guessing correctly and making errors despite knowing the skill to construct the Bayesian Knowledge Tracing to model student knowledge.

Existing work mainly identifies student progress as a set of state changes made by a student regarding certain learning attributes and whether they match with the teacher expectations. However, such progress information is quite primitive. It is not sufficient to form indicators helping students and teachers to make improvement on learning and teaching, unless they pay extra cognitive efforts to manually extract more comprehensive progress information from the feedback. It is because learning attributes are not independent but may have certain causal relationships among each others, which can also be dynamically changed over time. In addition, at different learning stages, student progress may be governed by a different set of learning attributes. For example, a student may be expected to mainly train up with concept memorization at an early stage rather than focusing on the learning outcome of applying knowledge. However the situation will become in the opposite when a student is going through a mature learning stage. On the other hand, a teacher may need a higher level of student progress information, such as the performance distribution within a cohort, the portion of students meeting the teacher expectations, or whether a student or a group of students is/are developing certain learning skills, to support teaching approaches adjustment. Our work is developed to provide a comprehensive solution to address such complicated needs.

1.3.3 Student Grouping

The information about the progress of a group of students also contributes to analyze the learning characters or behavior of one type of students. Teachers can know the major character of a group of students and make teaching approaches accordingly. On the other hand, teachers compare progress individually and in a group, so that they can provide students accurate and detailed feedbacks, effective instructions. And it is also convenient for an individual student to know the student's own progress and what is the student's difference from the others.

There are many criteria for grouping students. Some works simply group students by their attribute levels. Martineau et al. [Mart07] groups students by their knowledge levels, and then recommends different learning tasks to different levels of students. Reference [McMa07] groups elementary student with different levels of writing skill and uses writing assessments to examine the criterion validity and the sensitivity of growth. So that to make sure that students are progressing towards writing standards, to identify those who struggle, and to inform instruction aimed at improving students' writing proficiency. Reference [Bisw10] analyzes the student distributions of their misconceptions. A student may have a misconception when the student builds up the relationship of two knowledge concepts incorrectly. Students have the same misconception are grouped together to analyze how they understand knowledge. However, it is not enough to analyze the performance of a group of students who have only one common attribute. Sometimes, students' progress is affected only when combined attributes act together. Brusilovsky [Brus04] groups students with similar knowledge backgrounds and also with the same knowledge level that they want to achieve, and then they could be provided with the same navigation support of learning materials. However, students with different learning abilities would still being grouped together, so the learning materials may not appropriate to everyone.

We find out that existing works just group students whose attributes are either all good or all bad, while miss the effect of the other situations. However, they do not consider about the other patterns of attribute distribution. It is more intelligent to synthetically consider several aspects of student attributes, no matter if students are good at all of them or bad at all of them, as long as they keep the similar performance. It is not necessary to group all good students together and all bad students together. For example, according to students' performance, students with good communication skill, good listening skill and bad writing skill maybe grouped together for activity like 'debating', but students with bad communication skill, good listening skill and good writing skill would be considered as another group for activity like 'summary report'. In fact, some attributes are related to each other, and only the same attributes cannot represent student behavior patterns. Students with similar ability distribution should be the better way that is used to group the same type of students.

1.3.4 Learning Resources Construction

To support students learning effectively, relevant LRs should be identified and delivered in a proper sequence based on student needs and knowledge backgrounds. Farrell et al. [Farr04] proposes using Web resources as LRs without requiring teachers to create LRs. Suitable Web resources are selected based on certain student specific criteria, including topics to study, learning preferences and learning constraints, e.g. available study time. Dolog et al. [Dolo08] also allows students to search LRs for learning. However, the method in addition performs a query rewriting based on student profiles, which describes student learning preferences and learning performance (which indicates student knowledge level), so that students only need to focus on what they want to learn and the system will take care of the suitability of every LR, which matches the student searching criteria. Melia and Pahl [Meli09] proposes a more comprehensive modeling of LRs, where each of them is designed to associate with a concept, a knowledge type (verbal information or intellectual skills), and a knowledge level. LRs are connected based on concept relationships, where teachers manually define prerequisite among concepts. However, such relationships are not fine enough to support the arrangement of individual LRs in a proper sequence for delivery. Reference [Acam11] characterizes LRs based on subjects and organizes LRs by ontology-based subject relations, including part of, prerequisite, and weaker prerequisite relations. They form the basis for both determining the delivery sequence of LRs and selecting suitable LRs according to the student preferred subjects. However, subject information is too coarse that each subject is associated with many LRs, making precise learning path hard to be generated.

1.3.5 Learning Path Generation Algorithm

Given that LRs are properly modeled, a learning path generation algorithm can be used to deliver LRs for students to learn. Farrell et al. [Farr04] allows students to submit queries selecting suitable LRs. The selected LRs will then be ordered by the topics and the instructional methods that they belong to, respectively. As structures of LRs and relationships among LRs, which are critical to the control of student cognitive workload in learning, are not considered, learning effectiveness cannot be guaranteed. Karampiperis and Sampson [Kara05] models the structure among LRs based on a hierarchy of topics, which are defined by the ACM Computing Curricula 2001 for Computer Science. The method initially generates all possible learning paths that match the student goal. It then selects the most suitable one for a student to follow by considering the student cognitive characteristics and learning preferences. Although the relationships among LRs are essentially constructed manually, learning effectiveness is better addressed. Chen [Chen08] models the relationships among LRs based on an ontology-based concept map, which is generated by running a genetic algorithm on a set of student pre-test results. The method successfully works out the prior and posterior knowledge relationships of LRs, so that LRs can be delivered based on their difficulty levels and concept relations to reduce student cognitive workloads during the learning process. However, the relations of LRs are provided by the concept relations. In this way, they can only make sure the concepts in the learning path are continual, but the LRs may be not continual. It is necessary to provide students continual LRs through the learning path.

1.3.6 Test Generation

Student assessment is embedded into the learning process of each piece of LR, allows us to determine whether a student has completed learning a certain piece of knowledge with a proper level of understanding. The assessment result provides a means for updating student profiles regarding students' knowledge levels and completed knowledge concepts. In order to guide students to approach the most appropriate learning activities, help them to improve their performance, and then reach the learning goals, we need to know how well students perform during the learning process, so it is necessary to track their learning progress, evaluate their performance. Learning outcomes are given by ranks [Cood09, Ma00], scores

[Yang05 and Kwas08], or both ranks and scores [Liu05], feedback [Guzm07], or abilities of learner [Chen05, Dolo08] according to the level of acquired knowledge [Cood09], the spending time and effort [Cood09], or the number of correct questions [Chen08A] with tests or questionnaires.

To evaluate students' learning performance, existing work has developed ways to collectively model the students' understanding on knowledge. Huang et al. [Huan07] requires teachers to manually plan two formative assessments for each unit of learning, and a summative assessment in the end of learning path. The two formative assessments cover the same knowledge using different questions. The first formative assessment calculates students' scores and analyzes their learning situations. And the second formative assessment ensures students understand the concepts rather than memorizing the answers. In [Chen08A], the testing questions are also manually designed by teachers based on course materials and stored in testing question database. Questions are randomly selected from the testing question database to generate a pre-test. And the incorrect test results are used to select suitable courseware to plan the learning path. But these methods requires teachers to manually design the test, so [Cola10] provides an automatic method to measure student performance with a Bayesian approach which selects a set of questions associated with every network node to identify if a student can correctly form the knowledge concepts. However, these questions focus on single node, which cannot reflect if students can build up the relations in between and understand different aspects that relate to a knowledge concept. Building up the whole knowledge network can help students to understand knowledge concepts from the Marco view, and make them to relate other knowledge concepts more easily. But current works fail to achieve this advantage.

1.4 Challenges

The discussion in the last section motivated us to work on the construction of learning path, but there are some challenges need to be solved. This section discusses about the technical problems that we need to address. Though a lot of novel ideas in this area have been proposed in recent years, learning path construction and student progress measurement are still having some problems.

(1) **How to construct appropriate learning resources**? In order to help students to achieve their learning outcomes, they are required to study corresponding learning resources. Although it will be straightaway to acquire suitable learning resources from authentic institute, or to create them by designers, it is either expensive or very time consuming. These ways can only acquire limited resources, and sometimes, the learning resources are out of date. In order to save teachers' efforts, it is necessary to automatically generate learning resources. There are plenty of Web resources that can be obtained from authenticated Web sites and also can help students to achieve their learning

outcomes. We can directly use them rather than manually create learning contents. However, these Web resources are lack of correlations in between. In order to find out their relationships and to generate a well-structured knowledge model with these Web resources, we still need to identify the attributes of each piece of learning resource including its knowledge domain, importance degree, correlation with a topic, and complexity.

(2) **How to construct appropriate learning approaches?** The way to deliver knowledge elements indicates the way of how to learn by organizing learning activities into a learning path. Existing learning path generation methods [Chen06, Farr04, Kara05, Liu05, Limo09] mainly focus on the mechanism to produce the entire structure of a learning path. They use students' mastery of the prior knowledge and certain UoL selection constraints, such as mandatory UoLs, duration of study, or student learning preference, as the criteria to select suitable UoLs. Pedagogically, existing learning path generation methods only cope with part of learning needs. They do not properly consider teaching approaches, which are related to the way that a UoL is delivered and the type of activity that may help a student to learn a UoL effectively, and types of assessments, which are related to the skills that the student needs to acquire. These deficiencies affect the quality of the constructed learning paths in terms of the effectiveness of knowledge dissemination and the precision in assessing the student's learning performance.

Because students are assessed depending on different learning outcomes required by courses, the designing, managing, delivering, and organizing learning activities should be carried out based on the learning outcomes. Constructing learning path involves three issues: (1) setting up the learning outcomes of the learning activities in the learning path; (2) designing and managing learning activities; and (3) how to deliver or organize learning activities. In order to design and manage learning activities, existing works, such as, SCORM [Stec05], IMS Learning Design (IMS-LD) [Hern06, Amor06], and Learning Object Meta-data (LOM) [Chan04, Neve02], generate the whole structure of learning activities which are designed in terms of specific different learning contents or teaching approaches, rather than being designed in terms of the learning outcomes that are independent of subjects. And also, these specifications fail to involve a feasible assessment that can apply to different subjects and different forms of learning activities. In order to deliver learning activities, technologies like [Kazi04, Stec05] come with a hierarchical structure, and require teachers to pre-define rules to control the sequence, selection, or prerequisite of learning activities. Technologies acting like containers to define how different types of information, such as learning outcome, activities, resources, can be put together and control the workflow of their delivery. However, they do not provide facilities helping teachers to work out how the students can be assessed in terms of learning outcomes, and how a teacher delivers a course in terms of teaching approaches.

(3) **How to improve learning quality**? In order to measure student learning progress, other existing work usually identifies student learning progress by scoring subject specific attributes or by determining status about task completion, which are too simple to suggest how teaching and learning approaches can be adjusted for improving student learning performance. As there are too many student attributes, it is impossible to consider all of them, and it is not practical to integrate all attributes to fit any kind of progress analysis. Designers can set some learning outcomes in each learning activity for students to achieve and gain knowledge and skills. However, it is not easy to automatically generate the test to evaluate students' understanding according to their tailored learning resources, which can make sure students master the knowledge or skills during the process.

1.5 Research Objectives

In order to address the challenges discussed above, we need to achieve the following research objectives. In this monograph, we focus on constructing the representation of learning path as well as its generation to assess, guide, and analyze students learning progress, which shows them what to learn and how to learn. We show our research objectives as follows.

- To design the learning activities based on learning outcomes as the UoLs of a learning path, to evaluate student learning performance by both subject-specific and generic skills, in this way we can provide more comprehensive guidance of student progress. Also, to explicitly formulate the setting of pedagogy and learning outcomes, so that the learning activities are adjustable, fine-grained, and can adapt to different teaching approaches, and also offer a formal definition of the way to deliver learning activities.
- To select the most appropriate learning resources for personalized learning path, and show the way of how to learn these learning resources in a proper sequence, so that we can meet the needs of different types of students according to their learning preferences, learning abilities, and knowledge backgrounds, etc. Especially, to adaptively update the learning path, we also need a test generation scheme to automatically generate tests according to the contents of learning resources, so that we can evaluate students' learning performance and deliver them with the best learning resources that fit their learning abilities.
- To monitor student learning progress on various aspects including performance and non-performance related aspects, analyze the causal relationships of these aspects and how these attributes affect student learning performance, so that we can easily manage student learning progress, help teachers to modify teaching approaches, and help students to improve their learning qualities. And also, we need to evaluate students' achievements to see if they can have a balanced development on all required student attributes.

1.6 Contributions

In brief, there are three major contributions in this monograph in order to achieve these research objectives.

- In order to find out the learning approaches and answer the research question of how to learn, we have developed a fine-grained outcome-based learning path model that allows learning activities and the assessment criteria of their learning outcomes to be explicitly formulated by the Bloom's Taxonomy [Bloom, Bloo56]. Hence, provided with different forms of learning activities, pedagogy can be explicitly defined and reused. Our model can also support the assessment of learning outcomes related to both subject-specific and generic skills, providing more comprehensive student learning progress guidance and evaluation.
- In order to find out the appropriate learning resources to construct the learning path, loosely connected Web resources obtained from the Web have been formed to well-structured learning resources based on Association Links Network (ALN) to construct a teacher knowledge model (TKM) [Mish06] for a course and generate the personalized learning path to help students to achieve higher master level of knowledge. Our model automatically constructs the learning path in three different abstraction levels of ALNs, i.e. topic, keyword, and learning resource ALNs, which allows students to understand the relationships between learning resources through the three abstraction levels, and helps students to minimize their cognitive workloads. On the basis of a learning resource retrieved from the TKM, we automatically construct a test to assess students' understanding based on a test generation scheme which saves teachers a lot of efforts.
- In order to answer the research question of how well students have learned, we propose a set of Fuzzy Cognitive Map-based student progress indicators. We can monitor student learning performance and analyze the factors that affect student learning performance and comprehensively describe student learning progress on various aspects together with their causal relationship. Our model is based on student learning performance related attributes (PAs) as well as non-performance related attributes (NPAs) to model student learning performance and their potentialities to make progress.

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Chapter 2
Educational Theory

Learning theory is used to support the construction of learning path in e-learning for different types of students using different types of teaching approaches and also the generation of the learning resources as the learning contents. We assess student learning progress to determine their learning qualities. The following theories involve the introduction of learning theory to support our research, e-learning to introduce the research application in this area, learning taxonomy as the criteria of learning outcomes, learning styles for different types of students, learning modes for different types of learning approaches, student assessments for different approaches to evaluate student learning performance, Association Link Network to introduce how learning resources relate to each other, and system development tools of the research to introduce the used programming techniques. Given this information, readers can have a better knowledge background before starting to understand the main research of learning path construction in e-learning and the analysis of student learning progress.

2.1 Learning Theory

Learning theory [Band77] is the foundation of this monograph, which supports all the learning processes and is used to guide the design of learning systems. Learning theory describes how information is absorbed, processed, and retained during the learning process. There are three main categories of learning theory including behaviorism, cognitivism, and constructivism. Behaviorism focuses on achieving the objectively observable behavior by repetition of desired actions. Cognitivism looks beyond behavior to explain how the learning happened in our brain. Constructivism views learning as a process in which a student actively constructs or builds new ideas or concepts. Our monograph is developed based

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_2

on the constructivism learning theory. Constructivism learning theory [Coop04, Fran06] requires students to construct knowledge in their own meaning, to build up knowledge concepts based on prior knowledge and their experience, to enhance their learning through social interaction, and to develop learning through authentic tasks. During constructivism learning, students achieve learning outcomes by attempting to address problems when they find their expectations are not met, so they need to resolve the discrepancy between what they expected and what they encountered [Lefo98].

In the learning theory of constructivism, each student is considered as a unique individual with personalized needs, learning styles, learning preferences, knowledge levels, and knowledge backgrounds, which is complexity and multidimensional. During a typical constructivist session [Coop04], students work on problems and teachers only intervene them to guide them in the right direction. Students could provide different responses to learning, e.g., they are involved in an active learning process, and they are using critical thinking to challenge, judge knowledge, and learn from it. Under the learning theory, teaching approaches are designed according to these learning outcomes. With the help of techniques in e-learning, the learning process, which emphasizes that knowledge is shared between teachers and students, does not focus on the teacher-centered learning environment, but put more emphasizes on self-paced learning by providing access to education at any time, any place, and taking into account students' differences.

2.2 e-Learning

E-learning aims to support learning and teaching, transfer knowledge and skills through the Web and electronic machines. E-learning techniques provide various forms of electronic tools and platforms, teaching and learning approaches, learning environments, etc. Current research in e-learning mainly focuses on several broad aspects, such as *technology-enhanced learning*, *learning resource organization and standardization*, and *e-learning platforms and tools*. *Technology-enhanced learning* [Wang05] is technology-based learning and instructional systems, where students acquire skills or knowledge with the help of teachers, learning support tools, and technological resources. Technology-enhanced learning investigates the use of information and communication technologies to help students to learn effectively through a course of study by pedagogically making learning contents more accessible and providing students with better learning environments. *Learning resource organization and standardization* [Totk04] design models for organizing learning contents, so that the contents can be easily adopted by different e-learning systems and reused in various instructional contexts. On the other hand, *e-learning platforms and tools* [Dagg07], also known as virtual learning environments (VLE), use a mix of communication technologies and focus on the design and development of the hardware and software components of e-learning systems over the Web 2.0 for two-way interaction. *Adaptive e-learning* *methods* [Jere10] tend to find out an effective way to guide students to learn according to students' interests, so that the learning process could be adjusted for different students.

This monograph of learning path construction and the analysis of student learning progress are concerned with learning using electronic devices and the Web. We discuss different types of learning and different types of e-learning systems in this section to help reader to better understand how the learning is carrying out, and more specifically, how the e-learning is carrying out.

2.2.1 Types of Learning

Learning has gone through several stages where learning is traditionally supported by face-to-face teaching, and now with the help of communication and information technologies, new forms of learning, such as web-based learning, have been developed. However, traditional learning does not allow students to learn at any time and at any place, and web-based learning lacks of interaction between teachers and students. Blended learning is developed by combining the traditional learning and web-based learning to provide a better learning approach. Our monograph can be applied to both web-based learning and blended learning by providing a user-friendly intelligent tutoring system to construct learning path as well as to analyze student learning progress.

2.2.1.1 Traditional Learning

Traditional learning is teacher-centered learning, where teachers interact with students face-to-face in classroom. Traditional learning focuses on teaching, not learning. The knowledge taught in traditional education can be used in instructional design, but cannot be used in complex problem solving practices. It simply assumes that what a student has learned is what a teacher has taught, which is not correct in most cases.

2.2.1.2 Web-Based Learning

Web-based learning is self-paced learning, which requires students to access Internet via devices like computers. The learning is beyond traditional learning methodology. Instead of asking students to attend courses and read printed learning materials, students can acquire knowledge and skills through an environment which makes learning more convenient without spatial and temporal requirements. Web-based learning applications consider the integration of user interface design with instructional design and also the development of the evaluation to improve the overall quality of web-based learning environment [Chan07].

Web-based learning is different from the term of computer-based learning, which also uses devices like computers, but does not have to require students to access to Internet during the learning process.

2.2.1.3 Blended Learning

Blended learning combines traditional learning with computer-based learning, which creates a more integrated e-learning approach for both teachers and students. The aim of blending learning is to provide practical opportunities for students and teachers to make learning independent as well as sustainable. There are 3 parameters that should be considered in a blended learning course, which are *the analysis of the competencies*, *the nature and location of the students*, and *the learning resources*. Also, blended learning can be applied to the integration of e-learning with a learning management system using computers in a traditional classroom with face-to-face instruction.

2.2.2 Types of e-Learning

With the help of technologies and electronic media, e-learning makes the teaching and learning more effectively. Teaching and learning could be approached at any time and any place. E-learning systems have actually been well developed and have different types including traditional e-learning system, adaptive e-learning system, intelligent tutoring system, and service-oriented e-learning system. Traditional e-learning [Dagg07] has simplex design which fails to provide more flexible ways of learning, such as personalized learning, active learning, and online interactions between teachers and students. Adaptive e-learning [Shut03] focuses on student characteristics, such as learning styles, knowledge background, and learning preferences, which makes the learning to be applied to different teaching approaches for different types of students. Instructional design system [Gust02] contains 5 phases of *analyze*, *design*, *develop*, *implement*, and *evaluate*, which aims to determine student learning states, define learning outcomes, and provide teaching strategies. Intelligent tutoring system [Murr03] does not only focus on the sequencing mechanisms of curriculum delivery, so that students know how to learn rather than just what to learn, but also applies AI to customize teaching approaches according to student's needs in order to optimize learning of domain concepts and problem solving skills. Service-oriented e-learning [Jamu09, Su07] provides with different Web services, so that both teachers and students can access the e-learning system and use different functionalities. We briefly introduce them as follows:

2.2.2.1 Traditional e-Learning System

Traditional e-learning separates teachers from students and also separates students from students; the teaching and learning carry out over the Internet or through computer-based technologies [Stiu10]. Traditional e-learning cannot provide adaptive learning technologies, which needs a team that has advanced skills, such as programming, graphic design, or instructional design to improve the learning system and requires course creator to create graphics, simulations, and animations. Teacher also needs to design learning contents for constructing courses. Learning management system (LMS) [Brus04] is an integrated traditional e-learning system that supports a number of learning activities performed by teachers and students during the e-learning process. LMS aims to deliver online courses to students and try to keep students' learning progress on the right track, but LMS is not used to create learning contents. Students can use it for learning, communication, and collaboration.

2.2.2.2 Adaptive e-Learning System

Students have different knowledge background, knowledge levels, learning styles, learning preferences, and also different misunderstandings and learning outcomes, etc. It will become a very huge work for teachers to design the learning contents and the learning activities, and to provide with different teaching approaches and different feedbacks. The e-learning system is considered adaptive [Jere10] if it follows student behaviors as well as interprets them, makes conclusions about students' requirements and their similarities, adequately represents them, and finally impacts students with the available knowledge and dynamically manage the learning process. Adaptive e-learning system has the adaptability toward students' needs, the reusability of learning activities, and the effective design of learning contents. Our monograph can be applied to adaptive e-learning system as our research also constructs learning resources for different types of students and designs learning paths to support different teaching approaches.

2.2.2.3 Instructional Design System

Instructional design system is a system of determining student learning state, defining the learning outcomes, and also providing teaching strategies for knowledge transition, which aims to improve learning performance [Reis01]. Instructional design is learner-centered which focuses on current learning states, needs, and learning outcomes of students. The learning outcomes of instructional design reflect students' expectations for the learning, which expect students having the ability of applying knowledge or skill in some learning environments.

The procedure of developing instructional materials provides us the guidance and requirements of designing a qualified e-learning system. The typical instructional design system [Gust02] includes five phases including *analyze*, *design*, *develop*, *implement*, and *evaluate*. *Analyze* phase requires teachers to collect information about students, learning tasks and learning outcomes, and then classify the information to make learning contents more applicable. *Design* phase composes the expected learning outcomes and corresponding tests through learning tasks. *Develop* phase generates learning contents based on the learning outcomes. *Implement* phase refers to how to deliver the instructions for students to learn. *Evaluate* phase ensures that the learning contents can achieve the learning outcomes through both summative and formative assessments.

2.2.2.4 Intelligent Tutoring System

Intelligent e-learning system brings the artificial intelligence (AI) technology to the current e-learning system together and products a personalized, adaptive, and intelligent service to both teachers and students. Intelligent tutoring systems (ITS) use AI to customize teaching approaches according to student's needs, which is trying to optimize learning of domain concepts and problem solving skills. Our monograph can also be applied to ITS, because the proposed work provides adaptive teaching approaches, personalized learning resources, and intelligent student progress indicators. ITS [Murr03] are computer-based instructional systems, with instructional contents organized in the form of learning activities that specify *what to teach* and teaching approaches that specify *how to teach*. They make inferences on student learning progress and offer instructional contents and styles of instruction adaptively. Instructional contents can be broadly categorized into two main types [Bigg07]: declarative knowledge, i.e., facts or concepts, and functioning (procedural) knowledge, i.e., how something works. Early ITSs, such as SCHOLAR [Carb70a], focus only on the modeling of declarative knowledge and cannot properly support the training of procedural and problem solving skills. Newer ITSs, such as DNA [Shut98], incorporate the modeling of functioning knowledge to address this issue.

To identify a suitable teaching approach, an ITS should understand the learning progress of a student and, more ideally, consider student learning styles [Feld88, Li10] as well. In existing ITSs, such student information is commonly maintained as a *student model* [Brus07, Elso93] and updated by some *inference algorithms* [Chen06, Cona02]. Traditionally, the student model is typically formulated in the form of a *knowledge model* [Brow78, Carb70b] to maintain the set of learning activities that a student studies. Student learning progress is then evaluated by checking the portion of expert knowledge that a student has acquired. However, this model fails to formulate errors or misunderstandings made by the student. To address this problem, the bug-based model [Brow78] is proposed, which applies rules to determine the difference between the expected and the actual ways to be used for problem solving when studying a piece of knowledge. This model essentially evaluates the problems in understanding made by a student. On top of the student model, inference algorithms are applied to determine or predict the student learning performance over a course of study based on some probability information. Popular choices of inference algorithms are the *Bayesian networks* [Cona02], which perform inferences based on some precondition information, particularly the previous learning performance of students, and the *item response theory* [Chen06], which performs inferences based on the probability information of the responses made by students when conducting certain assessments.

2.2.2.5 Service-Oriented e-Learning System

Service-oriented system for e-learning describes a concept of e-learning framework which supports e-learning applications, platforms, or other service-oriented architectures. Service-oriented e-learning system [Jamu09, Su07] provides Web services, such as assessment, grading, marking, course management, metadata, registration, and reporting, in order to produce more functionalities for the e-learning system. It aims to produce reliable Web services that can be applied to different operation systems. Users can access these services through the Web. While our research supports such an e-learning platform where teachers can design and manage adaptive learning paths, personalized learning resources can be generated for each student and also student progress can be graphically presented.

2.3 Learning Taxonomy

Learning taxonomy provides the criteria of assessing student learning performance to see if students can achieve their learning outcomes. Learning outcomes are learning objectives that students are expected to achieve at the end of learning, which could be cognitive, skill-based, and affective learning outcomes. Learning taxonomy [Full07] includes three domains, *cognitive*, *affective*, and *psychomotor*, where each domain evaluates learning outcomes in several levels. Learning taxonomy guides teachers to design courses on the basis of achieving these learning outcomes as well. The most common learning taxonomy is Bloom's taxonomy which we have applied in this monograph. Because it can assess knowledge, attitude, and skills, it can be applied to all disciplines. There are also some other learning taxonomies slightly different from it, such as Gagne's taxonomy, SOLO taxonomy, and Finks taxonomy. Gagne's taxonomy does not only cover the 3 categories of Bloom's taxonomy, but also involve another 2 categories of verbal information, intellectual skills. SOLO taxonomy divides learning outcomes by 5 learning stages rather than independent categories. And Finks taxonomy considers learning as a cycle consisted of 6 aspects. We introduce each of them as follows:

2.3.1 Bloom's Taxonomy

Bloom's taxonomy [Bloo56] provides the criteria for assessments of learning outcomes which could be classified into three domains of knowledge, attitude, and skills, in this way it could be applied to all kinds of subjects. A learning activity should have its own learning outcomes, such as the knowledge level. Students can develop their knowledge and intellect in cognitive domain, attitudes and beliefs in affective domain, and the abilities to put physical and bodily skills to act in psychomotor domain.

The *cognitive* domain refers to intellectual capability, such as knowledge, or think, which has 6 levels from easy to difficulty including recall data, understand, apply, analyze, synthesize, and evaluation. The *affective* domain refers to students' feelings, emotions, and behavior, such as attitude or feel, which has 5 levels from easy to difficulty including receive, responding, value, organization, and internalize. The *psychomotor* domain also has 5 levels from easy to difficulty including imitation, manipulation, develop precision, articulation, and naturalization. The psychomotor domain refers to manual and physical skills, such as skills or do, which was ostensibly established to address skills development relating to manual tasks and physical movement. However, it also concerns and covers business and social skills such as communications and operation IT equipment, for example, public speaking. Thus, psychomotor extends beyond the originally traditionally imagined manual and physical skills.

2.3.2 Gagne's Taxonomy

The learning outcomes of Gagne's taxonomy [Gagn72] is similar to Bloom's taxonomy. However, Gagne's taxonomy divides learning outcomes into five categories, which are verbal information, intellectual skills, cognitive strategies, attitudes, and motor skills. Verbal information is the organized knowledge including *labels and facts* and *bodies of knowledge*. Intellectual skills refer to knowing how to do something including discrimination, concrete concept, rule using, and problem solving. Cognitive strategy is the approach where students control their own ways of thinking and learning. Attitude is an internal state which affects an individual's choice of action in terms of a certain object, person, or event. Motor skills refer to bodily movements involving muscular activity, including the learning outcome to make precise, smooth, and accurate performances with muscle movements. The learning outcomes are normally dependent on each other. There are always combined learning outcomes selected for completing a task.

2.3.3 SOLO Taxonomy

The SOLO taxonomy [Bigg07] stands for structure of observed learning outcomes, which describes the level of a student's understanding of a subject through five stages, and it is able to be used to any subject area. The first stage is *pre-structure* where students just acquire no structured information. The second stage is *uni-structural* where students capture simple and obvious aspects of the subject, but they still have not understood significant aspects. The third stage is *multistructural* where students make a number of relevant independent aspects but cannot connect them. The fourth stage is *relational* where students are able to identify the most important parts of the whole structure. The fifth stage is *extended abstract* where students can generalize another new application based on the structure constructed in the *relational* stage. The SOLO taxonomy is similar to the cognitive domain in the Bloom's taxonomy, which can be used not only in the assessment, but also in designing the curriculum in terms of the learning outcomes.

2.3.4 Finks Taxonomy

Finks taxonomy [Fink03, Fink09] is different from Bloom's taxonomy and SOLO taxonomy, which taxonomy is not hierarchical. It covers broader cross domains, which emphasizes on learning how to learn and includes more affective aspects. The learning process has 6 aspects in a cycle including foundation knowledge, application, integration, human dimensions, caring, and learning how to learn. In the aspect of foundational knowledge, students understand and remember knowledge. In the aspect of application, students train up skills of critical thinking, creative and practical thinking, and problem solving skills. In the aspect of integration, students make connections among ideas, subjects, and facts. In the aspect of human dimensions, students learn and change themselves, understand and interact with others. In the aspect of caring, students identify and change their feelings, interests, and values. In the aspect of learning to learn, students learn how to ask and answer questions, and become self-directed students.

2.3.5 Subsection Summary

We apply Bloom's taxonomy as the learning outcomes in our monograph. There are also a lot of works on Bloom's taxonomy. Reference [Naps02] applies Bloom's taxonomy [Bloo56] as well as other factors as follows: student learning progress, dropout rate, learning time, and student satisfaction. Limongelli et al. [Limo09] only chooses three out of the six levels: knowledge, application, and evaluation as the evaluation criteria. However, these evaluation methods still could not instantly tell students how to improve. Also, some work [Chen05, Dolo08, Cono05] considered student's ability as performance evaluation. Chen et al. [Chen05] evaluates student abilities based on the student's response to the recommended learning activity and modifies the difficulty levels of all learning activities which are considered as index to rank learning activities in order to update learning paths. However, a student's ability is just given by a single value. In [Dolo08], a student's abilities just limits to programming in Java or .NET, which cannot be applied to all situations. According to the research on learning abilities for evaluating student learning performance, it classifies these learning abilities into eight aspects: leadership, critical thinking, value-based decision making, logical reasoning, problem solving, oral communication skills, written communication skills, and lifelong learning. Each aspect contains several subaspects and making 74 subaspects in total. However, according to the research of psychology [Bart32], human abilities are divided into three groups: language, action, and thought with 22 subattributes in total. We found that there are some attributes that does not consider about, such as imagination, while there are some attributes in psychology that are not suitable to apply to general e-learning, such as speed, strength of power in the action group. Besides [Cono05], also distributes different ability requirements to learning tasks including too many skills (38 skills) without classification, and some of them are overlapped.

2.4 Learning Styles

Our work has developed learning progress indicators which addressed the needs of students with different learning styles. When we assess student learning progress, we expect students to handle different learning environments. If students can well perform different learning activities, they have the ability to handle different learning environments and have a balanced development. A learning style model classifies students according to their behavior patterns of receiving and processing information. Teaching style model classifies instructional methods according to how well they address the proposed learning style components.

According to the research of [Feld88], learning style contains five aspects. From the viewpoint of which type of information students prefer to perceive, there are sensors who prefer to solve problems using standard methods rather than unconventional methods, and intuitors who prefer to use innovated methods rather than repetition. From the viewpoint through which sensory channel external information most effectively perceived is, there are visual students who are sensitive to diagrams and graphs, and auditory students who are sensitive to words and sounds. From the viewpoint of which information organization students are most comfortable with, there are inductive students who are sensitive when given facts and observations, and underlying principles are inferred. Deductive students are sensitive when given principles and consequences and applications are deduced. From the point of view that how students prefer to process information, there are active students who prefer engagement in physical activity or discussion, or reflective students who prefer introspection. From the point of view that how students progress toward understanding, there are sequential students who learn in continual steps, and global students who learn gradually from the whole knowledge structure to more detailed concepts.

2.5 Learning Modes

In this monograph, we use different learning modes to design teaching approaches for different aims of training students. The learning has various forms, which does not only support individual learning but also support collaborative learning. In our monograph, we also need to use different forms of learning to construct different teaching approaches. Individual learning helps students to train them to solve problems on their own, and collaborative learning helps students to train them teamwork spirit. The most common way of learning is to work individually. Students have to work on their own to solve problems and reach the learning outcomes. Collaborative learning is a type of learning in which two or more people learn something together, where students can make use of peer's learning resources and skills. Collaborative learning includes collaborative writing, group projects, joint problem solving, debates, study teams, and other learning activities. Collaborative learning uses technology to define rules and roles, construct learning tasks, control and monitor the learning process, and support group interactions in a collaborative learning environment.

2.6 Student Assessment

As the aim of learning is to achieve learning outcomes, the learning path is constructed based on learning outcomes. In order to determine if students have achieved their learning outcomes, we need to assess their learning performance. Student assessment measures the level of student achievement on knowledge and abilities. The form of student assessment can be summative or formative [Osca11]. Information about student learning progress needs to be collected before, during, and after learning some learning activities [Feng09, Osca11]. Student learning progress can be expressed as growth rate [Bete09, Stec08] and overall improvement [Pets11]. In addition, prediction on student's future learning performance [Hanu05, Wiel10] can also be done. A teacher may review and enhance teaching approaches based on student learning progress [Stec05, Stec08].

By tracking student learning progress and evaluating student learning performance, we can guide students to approach the most appropriate learning activities as well as to help them to improve their learning performance and reach the learning outcomes in the end. Based on previous work, learning outcomes are given by ranks [Good09, Ma00], scores [Kwas08, Liu05, Yang05], or feedback [Leun07, Guzm07], according to different criteria, such as the levels of acquired knowledge [Good09, Leun07], the spending time and efforts [Good09], the number of correct questions [Chen08] with tests or questionnaires, or learning abilities of students [Dolo08, Leun07, Chen05].

Although [Leun07] can provide an instant feedback on student learning performance, the feedback can only tell if we should provide students the optional materials. In [Huan07], a student knows his/her misconceptions in solving a problem and the student's weak learning activities from a global test. However, this information is not enough to know the student's learning progress and cannot help the student to improve his/her learning performance. In [Ma00], the evaluation results would always be divided to several fuzzy grades from the "best" grade to the "worst" grade, and examples of fuzzy grades include "good," "pass," "fail," etc. Even if a student performs better than the course expectation, the student would still fail as long as the student is worse than the majority of students. In [Chen05], the evaluation tests student's satisfaction on the learning path. However, this work cannot promise the student to reach the learning outcome. Guzman et al. [Guzm07] provide a self-assessment test which can rectify misconceptions and enhance acquired knowledge. With a student's knowledge distribution model, the selected evaluation criteria determines questions and computes the expected variance of the student's posterior knowledge distribution. The test results provide an estimation of the student's knowledge level which is the minimum expected posterior variance. As they need to calculate the correct possibility and the incorrect possibility of a question, the answer has to be either true or false, but these results are too limited for the most types of questions. In short, these methods only consider if students can correctly understand knowledge in one way or another, but they ignore the assessment of balanced developments of students' knowledge and learning abilities.

Existing works [Chen08, Cola10, Huan07] have developed ways to collectively model the students' understanding on knowledge. Huang et al. [Huan07] requires teachers to manually plan two formative assessments for each UoL, and a summative assessment in the end of a learning path. The two formative assessments cover the same knowledge using different questions. The 1st formative assessment calculates students' scores and analyzes their learning situations. The 2nd formative assessment ensures students understanding the concepts rather than memorizing the answers. In [Chen08], questions are manually designed by teachers based on the course materials and stored in the question database. Questions are randomly selected from the database to generate a pretest. The incorrect test results are used to select suitable courseware to plan the learning path. However, these methods require teachers to manually design the test, then [Cola10] provides an automatic method to measure student learning performance by the Bayesian approach, which selects a set of questions associated with every network node to identify if a student can correctly form the knowledge concepts. However, these questions just focus on each single node, which cannot reflect if students can correctly build up the relationships between them.

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Chapter 3
Technical Definition and Concepts

3.1 Terminologies Definition in the Proposed Research

I would like to introduce some terminologies, which are all very important concepts of this monograph. This research improves the **E-Learning** systems and aims to help students to achieve their **learning outcomes**. We generate **learning resources** and construct **learning paths** based on **learning activities** to provide them what to learn and how to learn. We also measure their **learning progress** to provide more details about student learning to improve their learning qualities.

3.1.1 Learning Outcomes

Learning outcomes explain what students are expected to achieve at the end of a period of learning, which are expressed by the level of competence to be obtained by the students [Wage08]. Learning outcomes are measurable, so that they could be used to measure student learning performance, which could be cognitive, skill-based, and affective learning outcomes. Learning outcomes are always being defined by descriptive verbs [Nash]. For example, to define the terms, to compare the two ideas, to compute the possibility, etc. Learning outcomes are set to be the criteria of assessing student learning performance. Subject-specific knowledge and skills, and generic skills could be used to measure learning outcomes by assessing formative or summative assignments or examinations. For example, students are expected to describe/explain knowledge concepts and reach some knowledge levels [Chen06, Guzm07], to apply research skills [Feng09, Mitr01], or to develop some learning behaviors [Gres10]. However, learning outcomes in this work can only apply to limited aspects of learning, which cannot support different designs of learning activities and cannot be applied to different knowledge disciplines.

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3.1.2 Learning Resources

Learning resources [Kara05, Meli09] refer to the structured learning materials or learning contents that can help students to understand some knowledge concepts and achieve their learning outcomes. Learning resources could be represented by different types of media [Leac07], such as text, audio, or video, and are associated with attributes including knowledge domains, complexities, importance degrees, as well as the relationships among each other. These attributes of learning resources can facilitate course design that is adaptive to students [Kara05] who have different knowledge backgrounds, knowledge levels, etc. In fact, it is not easy to automatically obtain these attributes from complex and loosely connected learning contents and to use them to form well-structured learning resources. It is not enough to only identify suitable learning resources for a student. It is also necessary to provide students with the relationships among learning resources, because these relationships explain how knowledge concepts are related to each other, helping students to gain a better understanding and improve their learning performance.

3.1.3 Unit of Learning

Unit of learning (UoL) is a term very known in E-learning and is used to refer any delimited educative or training piece like a course, a module, a lesson, etc. [Gome09]. UoL represents the minimum significant educational piece, which contains learning content, learning objectives, learning method, and other resources [Ivan09]. The instructional design is the key element in a UoL and is basically what it is tried to be modeled, and the other elements are necessary and complementary parts [Gome09]. In order to build a UoL, IMS learning design [Hern06, Amor06] describes and implements learning activities based on different pedagogical methodologies, including group work and collaborative learning. In our research, a UoL is also the basic element to construct a learning path.

3.1.4 Learning Activity

A learning activity (LA) is a UoL guided by certain teaching approaches based on some learning outcomes, which is used to construct teaching and learning approaches. It can be formulated in different forms to facilitate different learning environments in which different kinds of learning activities require different learning styles and different learning outcomes. During a LA, a student will follow a particular teaching approach that applies to the student's own characteristics, and achieve some learning outcomes in the learning process. A LA is independent of learning contents, which makes the pedagogies being reused in different knowledge disciplines. The way to deliver the learning activities indicates a sequence of learning.

Existing works [Chen06, Farr04, Hern06, Limo09, Liu05] generally adopt lecturing and Q&A as learning activities. However, the situation can be complicated in practice. First, each LA may be very different in nature from the others, so it requires to be delivered through a different form, such as lecture, presentation, practical, etc. Also, each LA can be carried out through different learning modes, such as individual learning, and collaborative learning. A specific or even multiple assessment methods may be required to determine the student's learning performance. Second, in different subject disciplines, even the same type of LA may need a very different kind of assessment method. For example, a "practical" activity for a programming course may focus on training up the students' problem-solving and application skills, while the same activity for a piano course may focus on fingering and sight-reading. Such practical requirements are so complex that it becomes difficult to implement a learning path construction system that generically addresses all of them. This explains why most existing methods allow only lecturing and Q&A as learning activities, even though this significantly restricts their usefulness.

During a LA, a student can achieve some learning outcomes by learning the content of it. SCORM [Su06] and IMS Learning Design (IMS-LD) [Hern06, Amor06] are the major existing standards for designing learning path on the basis of UoL. The sequencing of SCORM controls the order, selection and delivery of a course, and organizes the UoLs into a hierarchical structure. The UoLs are actually designed based on given learning materials and only model a single student's need. However, SCORM only concerns learning contents and the sequence of UoL delivery, but not considers teaching approaches and different types of learning outcomes evolved in a UoL. IMS-LD is a data structure holding information about the UoLs and their learning outcomes. It comprises UoLs modeling what to learn, and supports UoLs modeling how to learn, based on the learning outcomes of UoLs. A UoL and its contents are separated, so that the designed UoL can be reused. However, IMS-LD needs teachers to define the pedagogical structure without given clear guidance.

3.1.5 Learning Path

Learning path (or *curriculum sequencing*) construction [Brus92] is fundamental to the education process, which comprises a series of learning activities for the student to build up certain knowledge and skills. It refers to the organization of learning activities in a proper sequence, so that students can effectively study a subject area. Different forms of learning activities can support the implementation of different teaching approaches in a learning path. Obviously, if we can adaptively produce a learning path according to a student's learning performance and preferences, it will help the student to master knowledge and skills more efficiently.

There are different methods proposed for designing learning paths. Melia and Pahl [Meli09] directly generate the best learning path for different students within their Courseware Model (CM). However, the CM only allows UoLs to be organized one after another according to the student model, such that students cannot follow UoLs in parallel for learning. In practice, some UoLs are complementary to each other, where students can learn more efficiently if students can study those UoLs in parallel. In addition, the student model only considers students' initial knowledge and learning outcome. Many other critical factors, e.g., learning style, that affect students' learning preferences are not considered. Liu and Yang [Liu05] adopt an incremental approach. They first identify the key elements of a learning path (the initial, the target and the essential UoLs) and then incrementally work out the successive UoLs connecting these key elements. This method also considers asking a student to retake a UoL or to follow a re-designed learning path if necessary. Hernandez-Leo et al. [Hern06] propose a semi-automatic method that allows teachers to design the learning path based on pre-defined Collaborative Learning Flow Patterns (CLFPs), where a CLFP involves a flow of tasks. However, CLFPs do not support flexible combination of these tasks. So, if a teacher chooses a template pattern, a student has to use all the tasks included in the pattern.

3.1.6 Learning Progress

Learning progress reflects the changes of student learning performance in different aspects over time, which is the process of determining the learning performance of the student according to learning outcomes [Good09]. Student learning progress not only shows how much knowledge and how well a student has learned, but also provides with the changes of the student's learning performance, which has become a popular topic over time [Mart07]. During the learning process, student learning performance is changing after a period of learning. Their learning abilities and knowledge levels may be improved or may stay as the same. It would take different efforts for different students to make the same learning progress. We need to monitor student learning progress and analyze the contributions of different factors on their learning performance.

With the help of student learning progress, teachers can design learning path [Kwas08], adjust course settings (e.g. difficulty level, updating learning contents), update student profiles, group students who have the same learning style, (e.g. it may deduce that if there are a group of students who perform better on 'Analyze' knowledge level, they are more likely to be reflective students who prefer to process information through introspection.), and also provide better instructions to students. Teaching and learning can be improved according to student learning progress which is reflected from student or course attributes.

3.2 Concepts Proposed in the Monograph

We have evolved some variables for the building up of math models in the proposed methods. These variables are used to control our experiments, and see if they would cause changes to the experiment results. We also applied some variables, which can be obtained from our experiments, as the criteria to evaluate our work. We explain them as follows.

3.2.1 Teachers' Teaching Experience

In this monograph, teaching experience refers to how long a teacher has been a teacher. We consider it as a variable because teachers have different teaching experience may have different evaluation results about our prototype according to their teaching experience.

3.2.2 Teachers' Knowledge Discipline

Teachers' knowledge discipline refers to teachers' knowledge backgrounds, i.e. which subjects they teach. Also, teachers from different knowledge disciplines may use different teaching approaches. We consider it as a variable that may cause changes to their evaluation results.

3.2.3 Teachers' Satisfaction Score

In order to evaluate teachers' feedbacks from the questionnaire (Appendix A), we use teachers' satisfaction score to indicate their overall satisfaction on our outcome-based learning path model. Questions include if they are satisfied with the functionalities of the model, if the model can be easily understood, if it is easy to manage the model, etc. The answers of these questions are quantified by the 5-point likert scale, then we can calculate the overall teacher's satisfaction score by the sum of all these questions.

3.2.4 Importance of a Learning Path

The learning path construction method based on Association Link Network can automatically construct personalized learning path. However, in order to evaluate if the system recommended learning path is good enough, we consider the importance of the learning path as a variable, which is calculated by the sum of importance of each topic in the learning path. We can compare the importance of system recommend learning path and that of manually selected learning paths to see which one is better.

3.2.5 Learning Performance on a Learning Path

Learning performance indicates students learning quality, which we can use to determine if the system recommended learning path could contribute to student learning, and if the system recommended learning path is superior to manually selected learning path. We ask students, who use our system and who do not use our system, to do the same test. The learning performance is the overall score in the test.

3.2.6 Stability of Learning Performance

Considering that these participated students have different learning abilities, and also the learning resources have different complexities, the students may have similar performance on simple learning resources, because in which case, all students can provide correct answers. Or they may have similar performance on very complex learning resources, because none of them can provide correct answers. On the other hand, they may have quite different performance on the medium difficulty level of learning resource, because only students with higher learning abilities may provide correct answers. We use stability of learning performance to indicate if different students can have stable performance on the same learning resource. If we can improve the stability of learning performance, then it means that we can better help low learning ability students to improve their learning performance, so that they can have the similar learning ability with high learning ability students. The variable is collected from all students' learning performance on each piece of learning resource, more details about the formulation of this variable can be found in Sect. 5.6.2.

3.2.7 Student Learning Performance

Student learning performance refers to the performance on performance related attributes. We use it to monitor student learning performance changing over different attributes in the same stage of learning. Given the learning performance on different performance related attributes and which attribute will cause the changes of the student learning performance, both teachers and students can know students' strength as well as weakness and help them to improve correspondingly.

3.2.8 Student Development Balance Degree

We would like to find out if students have the potential to make further improvements. Teacher can decide to go on providing them corresponding learning resources if they have the potential. During the development of student learning ability, there are many non-performance related attribute. Student development balance degree indicates how well a student can handle different learning environments which require the student to have different non-performance related attributes. If a student has a balanced development on all non-performance related attributes, for example, the student is good at learning both concrete examples and abstract concepts, or the student has no difficulty in learning knowledge presented in the form of either verbal, visual information or context, then the student can perform better under different learning environments. We consider the development balance degree as a variable to indicate student progress potential to achieve more in the future.

3.2.9 State Value of a Student Attribute

We have applied two types of attributes to describe the characteristics of student learning, which include performance related attributes and non-performance related attributes. However, the performance of an attribute may cause effect on the performance of the other attributes. For example, if a student has good performance on the 'Responding' attribute, then the student probably prefers the learning style of 'Active' (Ref. Sect. 2.4) when the student processes information. In order to calculate the overall strength of impact of an attribute on all the others, we use the 'state value' of the attribute to measure the impact. Each state is actually the value of a node in the Fuzzy Cognitive Map, which represents the causal relationships between these nodes and how they affect each other.

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Chapter 4
Fundamental Theories and Development Tools

4.1 General Research Methodology

The general research methodology we have applied includes both qualitative method and quantitative method, which is used to verify if teachers and students are satisfied with our research work as well as to verify if our research work can provide with better teaching approaches. Research methodology also explains the methods that we use to collect quantitative data and/or qualitative data.

4.1.1 Qualitative Research Method [Wiki4, Schu03, Shie03]

Qualitative research is carried out to find out subjective assessment of attitudes, opinions, and behaviors, such as to understand meanings, experiences, ideas, and values. Normally, interviews are applied to describe and understand subjectively certain approaches.

Qualitative research involves collecting, analyzing, and interpreting data by observing what people do and say. Qualitative research aims to gain a qualitative understanding of the underlying reasons and motivations. Its sample only requires a small number of nonrepresentative cases, while the collected data are unstructured. In order to analysis data, qualitative research uses nonstatistical method. And the analysis results develop an initial understanding.

To conduct a qualitative research, there are mainly 4 steps:

STEP 1: Determine the qualitative research approach if necessary;
STEP 2: Determine the qualitative data collection method;
STEP 3: Qualitative data analysis; and
STEP 4: Report writing.

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Qualitative research method mainly includes narrative research, phenomenology, case study, ethnography, and grounded theory. We applied case study in this monograph to verify the proposed methods.

Case study research involved the study of an issue explored through one or more cases within a bounded system. It is a preferred method when

(a) how or why questions are being posed,
(b) the investigator has little control over events, and
(c) the focus is on a contemporary phenomenon with a real-life context.

Case study tries to illuminate a decision or set of decisions: why they were taken, how they were implemented, and with what result. It involves multiple sources of information and reports a case description and case based themes.

4.1.2 Quantitative Research Method [Wiki5, Schu03, Shie03]

The quantitative data are collected to measure variables and verify existing theories or hypotheses. The collected data are used to generate new hypotheses based on the results of different variables. Normally, questionnaires are applied to gather these statistic data.

Quantitative research involves the use of structured questions in which response options have been predetermined and a large number of respondents involved. Quantitative research aims to quantify the data and generalize the results from the sample to the population of interest. The sample should involve a large number of representative cases, while the collected data are structured. When to analysis data, quantitative research uses statistical method. And the analysis results would recommend a final course of action.

The nature of quantitative research is the use of statistic model to test the relativity between the independent variable and the dependent variable, and in turn to test the hypothesis and to deduce the cause and effect relationship between the variables. Quantitative research often contains the following steps:

STEP 1: to establish hypothesis and to determine the variables in the cause and effect relationship;
STEP 2: to use the reliable tools to measure and analyze the variables;
STEP 3: to test the hypothesis; and
STEP 4: to draw a conclusion.

Quantitative research emphasizes on the quantitative analysis and statistical calculation, including experimental method, quasi-experimental method, and questionnaire method. We applied experiment method and questionnaire to quantitatively verify the proposed research model.

4.2 Math Modeling Method for Learning Contents—Association Link Network

In our monograph, we need to find out the relationships of learning resources to form the knowledge structure model which is used to support the construction of learning path. However, the relationships of learning resources depend on the semantic features of learning resources. Our work is based on Association Link Network to identify these relationships. Association Link Network (ALN) [Luo08A] is a kind of semantic link network, which is designed to establish associated relations among various resources (e.g., Web pages or documents in digital library) aiming at extending the loosely connected network (e.g., the Web) to an association-rich network, which can support huge number of LRs to be built up automatically. Since the theory of cognitive science considers that the associated relations can make one resource more comprehensive to users, the motivation of ALN is to organize the associated resources that are loosely distributed in the Web for effectively supporting the Web intelligent activities such as browsing, knowledge discovery, and publishing.

ALN using association rules between concepts to organize the resource since the term *association* is used in a very particular sense in the psycholinguistic literature. However, most subjects cannot distinguish the exact semantic relations. The associated relations between resources in ALN are implicit rather than explicit, which make ALN more appropriate for incrementally building up. The challenge of building up ALN is about how to efficiently and exactly perform the association weights of the new coming Web resources.

ALN is composed of associated links between nodes. It can be denoted by $\text{ALN} = \langle N, L \rangle$ where N is a set of Web resources (e.g., keywords, Web pages, and Web topics). L is a set of weighted semantic links. As a data model, ALN has the following characteristics:

(1) **Associated relation-based link**. *Association relation-based link* is used in a very particular sense in the psycholinguistic literature. For example, the subjects respond more quickly than usual to the word *nurse* if it follows a highly associated word such as *doctor*. WWW uses hyperlink to interconnect Web resources for users freely browsing rather than for effective associated link. How to organize Web resources with associated relations to effectively support the Web intelligence activities becomes a challenge. ALN uses associated relations between Web resources to solve this problem.

(2) **Automatic construction**. Given a huge number of resources in the Web, it is unrealistic to manually build a network. Actually, ALN is automatically built up, which makes it suitable to represent the huge number of resources.

(3) **Virtualness**. ALN can be regarded as a virtual layer of Web resources, which is invisible to users. The operation of Web intelligence activities is implemented on this layer. Virtualness ensures the cross-media implementation of intelligent browsing, which clears the difficulty brought by different physical types of resources.

(4) **Rich Semantics**. Each piece of Web resource is represented by E-FCM with rich semantics. The links with weights between nodes represent the associated relations between Web resources.
(5) **Structuring**. By semantic computing, the disordered resources on physical Web layer are mapped to the well-structured ALN.

4.3 Math Modeling Method for Improving Learning Quality—Performance Inference Algorithm

As we need to analyze student learning progress by inferring how the learning progress is changing over particular aspect(s) of student attributes, we can find out the reason how to help students to improve efficiently. Previous works [Chen05, Feng09, Gres10, Lynn09] have qualified student learning performance with different inference algorithms. Normally, people assess students with a set of questions, then the performance is the evaluation results on these questions. But the difference is that they focus on different aspects to evaluate student learning performance. Item Response Theory (IRT) [Chen05] is the function of student ability based on major fields and subjects, which gives the probability that a student would have correct answers with a given ability level. Goal Attainment Scale (GAS) [Lynn09] is the function of a combination of attained goals and involves the expected correlation of the goal scales to make it adjustable. Change-Sensitive Rating Scale (CSRS) [Lynn09] evaluates student learning progress with a rating scale on a set of social behaviors including social skills (e.g., cooperate with peers) and competing problem behaviors (e.g., disruptive classroom behaviors). It focuses on computing the mean changes of student behaviors from the initial learning performance to posttreatment. An item is change-sensitive when the magnitude of change is larger than the threshold. Feng et al. [Gres10] presents that an individual student learning progress on subject-related skills changes over time with a linear mixed-effect logistic regression model. This model is to compute the probability that an individual student gives a correct answer at an opportunity of answering a question. It is the linear function of the effects caused by two learning parameters: one is how good the student's initial knowledge is and the other is the student's change rate of his/her learning progress.

Because the performance on some concepts/attributes may depends on the performance of some other concepts/attributes, more intelligent algorithms are required to represent the causal relationships among those concepts/attributes and to find out the main attributes that affect the learning progress. Which concepts or attributes are chosen for evaluation depends on the types of learning outcomes defined in the work. If the learning outcomes are just to achieve more knowledge, they may need to infer the causal relationships of concepts. If the learning outcomes are to achieve some student attributes, such as some kinds of learning abilities, then they need to infer the causal relationships of attributes. There are six popular algorithms that can structure the concepts/attributes in a graph:

– The *expert system* [Hatz10, Stud98] represents relationships between concepts in a tree structure where the top node of the tree indicates the goal knowledge, and the nodes on leaves indicate the rules. Goal knowledge is then inferred after several rule decisions.
– The *Bayesian Network model* [Cola10, Garc07, Dieg00] organizes the knowledge representations in a directed acyclic graphical, and the nodes in the model are conditional dependencies. They normally consider knowledge nodes or questions as the network nodes and then infer the causal relationship among them. Colace and De Santo [Cola10] applies *Bayesian network* to infer student learning performance, where questions are treated as the network nodes. *Bayesian analysis* measures the percentage of correct answers as well as incorrect answers in a subject, which supports for the measurement of cross-entropy to quantify the dependency weight between the questions. Although Bayesian network can infer the casual relationship among knowledge nodes, the inferred knowledge node cannot reflect back to previous knowledge nodes. They cannot be formed in a cyclic structure.
– The *Markov random field* [Zhu02] represents the structure of knowledge nodes within an undirected graph which supports both cyclic and acyclic graphs but does not support induced dependencies. And also, Nonadjacent nodes and neighbor nodes need to be conditionally independent.
– *Neural network* [Hatz10, Hayk99] infers causal relationships within a multilayer structure but does not support induced independence among concept nodes.
– The *Concept Maps* [Chen01, Zapa02] are connected with labeled arrows in a downward-branching hierarchical structure, which is an acyclic structure. The relationships between concepts show relationship such as "results in," "contributes to," or "is required by."
– *Fuzzy Cognitive Map* (*FCM*): As the structure is expected to reflect the causal relationships among knowledge nodes, the structure should be directed because one node is likely to affect other nodes or being affected by other nodes. On the other hand, the structure should be cyclic because some nodes may form a cycle. However, the above structures do not meet these requirements, but FCM [Liu99, Luo10] can represent such causal connections among knowledge nodes in a directed cyclic structure. FCM is a tool to represent social scientific knowledge. It computes the impact of the nodes and describes the nodes and the relations between these nodes, in order to analyze the mutual dependencies between nodes.

FCM method has been well developed and widely used in different areas including social science, economics, robotics, and computer assistant learning. Some works [Tzen10, Cai06, Geor04, Geor08] applied FCM to e-learning in order to infer the casual relationship among a set of factors. One example is to use the criteria for decision making as the concept nodes in FCM, such as [Tzen10]. It can be used as the reasoning tool to select the goal of what to achieve and the actions of how to achieve [Cai06]. Also, some works [Geor04, Geor08] infer student learning styles through FCM, where the learning styles reflect how students conceive information and also conceive which kind of information. To connect one attribute to another, FCM needs to compute the impact between two related attributes, which can be considered as the weights of the FCM. Basically, FCM methods have gone through three stages:

(1) The basic FCM [Tabe91, Geor08, Tzen10] predefines the weights with consistent values before applying FCM matrix to analyze the relationships among these knowledge nodes. Reference [Geor08] asks experts to describe the causal weights among the attributes every time. Also [Tzen10] always uses a predefined weight matrix, while the attribute values update according to their last statuses during iteration.
(2) Also, the weights could change under different concept models, as the dependences among concepts are different. A better method that is proposed to constrain the weights is the rule based FCM [Peña07]. It uses fuzzy "If-then" rule to increase or decrease the causal weights by a fuzzy interval.
(3) Later, an automatic scheme [Luo10] has been proposed to calculate the casual weights. Luo et al. [Luo10] applies FCM to build up a learning guidance model for students. It combines unsupervised learning and supervised learning to iteratively acquire new knowledge from data, but it still needs initial human intervention.

Although these current works monitor student learning progress and provide assessment results, they just focus on setting the evaluation criteria and more accurate grading scheme. There is still no such a tool could analyze student learning progress, find out the relations between different attributes, and see how these attributes affect the learning progress. Actually, FCM supports such an inference scheme that can infer student learning progress about how an attribute affects the others. All possible attributes could be considered as the nodes, and the effect of one attribute on one another would be the inferred causal relationships. So that both the teachers and the students would not only know whether the student makes progress but also know what can force the student to make progress. However, student attributes appear to have various changes for different students, different learning activities, or different subjects. In order to come out the inner relationships among these student attributes, it is not enough to infer them by only using FCM. It is necessary to integrate some similarity and different measurements to measure the related comparison targets.

4.4 Data Analysis Related Method for Experimental Verification

4.4.1 One-Way ANOVA [Chan14, Wiki1]

In statistics, one-way analysis of variance (one-way ANOVA) is a technique used to compare the means of three or more samples, which technique can only be used for numerical data.

The ANOVA tests the null hypothesis that samples in two or more groups are drawn from populations with the same mean values. Two estimates are made of the population variance σ^2. These estimates rely on various assumptions. The ANOVA produces an F-statistic, the variance between the group means should be lower than the variance of the samples, following the central limit theorem. A higher ratio implies that the samples were drawn from populations with different mean values.

One-way ANOVA is used to test for the differences among at least three groups. If there are only two groups of data to be compared, then the t-test and F-test are equivalent.

The results of a one-way ANOVA can be considered reliable as long as the following assumptions are met:

- Response variable residuals are normally distributed;
- Variances of populations are equal; and
- Responses for a given group are independent and identically distributed normal random variables.

The test performed by calculating two estimates of the variance, σ^2, of population distributions: the variance between the samples and the variance within the samples. The variance between samples is also known as the mean square between samples (MSB) and the variance within samples is also known as the mean square within samples (MSW). Both MSB and MSW estimate the variance of populations, σ^2. MSB is based on the values of the means of the samples taken from populations, and MSW is based on the individual values in the samples. If the means of the populations under consideration are not equal, the variation among the means of respective samples is expected to be large, and therefore, the value of MSB is expected to be large.

The value of the test statistic, F, for the ANOVA test is calculated as

$$F = \frac{\text{Variance between samples}}{\text{Variance within samples}} = \frac{\text{MSB}}{\text{MSW}} \tag{4.1}$$

This test statistic has the F distribution with degrees of freedom $k - 1$ and $n - k$, respectively, where k is the number of populations under consideration and n is the number of data values in all samples. The formulas for calculating MSB and MSW can be found in any introductory statistics text. The one-way ANOVA test is always right-tailed and the p-value is computed using the right tail of the F distribution curve.

4.4.2 Two Sample T-Test [Wiki2, Zhan14]

A t-test is any statistical hypothesis test in which the test statistic follows a Student's t-distribution under the null hypothesis. It can be used to determine if two sets of data are significantly different from each other and is most commonly applied when the test statistic would follow a normal distribution if the value of a scaling term in the test statistic were known.

A hypothesis testing as follows can be applied to determine whether μ_1 - μ_2 equals zero.

$$H_0 : \mu_1 = \mu_2; H_1 : \mu_1 \neq \mu_2 \tag{4.2}$$

where the hypothesis H_0 is referred to as the null hypothesis, while H_1 is referred to as the alternative hypothesis.

A two-sample location test of the null hypothesis such that the means of two populations are equal. Let X_1, X_2 be independently distributed as the normal distribution with sizes n_1 and n_2, means μ_1 and μ_2, and variances σ_1^2 and σ_2^2, respectively, where n_i ($i = 1, 2$) are known and μ_i, σ_i are unknown.

The statistics used in the two-sample t-test is given by the following equation. The statistics have the t-distribution in the case of null hypothesis.

$$t_0 = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} \tag{4.3}$$

$$v = \frac{\left(s_1^2/n_1 + s_2^2/n_2\right)^2}{(s_1^2)^2/(n_1 - 1) + \left(s_2^2\right)^2/(n_2 - 1)} \tag{4.4}$$

where $\bar{X}_1$, $\bar{X}_2$ are the means of X_1, X_2. s_1^2, s_2^2 are the sample variances corresponding to X_1, X_2. v is the degree of freedom of the t-distribution.

The test is defined by its critical region which is determined by the significance level α ($0 < \alpha < 1$). The significance level α is found under the constraint of the degree of confidence, which is used to estimate the reliability of an estimator. Given a significance level α, H_0 will be rejected if $t_0 > t_{\alpha,v}$, where $t_{\alpha,v}$ is the upper α critical point of the t-distribution with v degrees of freedom, i.e., $\alpha = \mathrm{P}(t_0 > t_{\alpha,v})$.

4.4.3 Likert Scale [Wiki3]

Likert Scale is one of the most often used scale for rating sum formula. Items that belong to same concepts or structure apply the way of sum formula for rating. Likert scale is normally used for questionnaires, which is the most widely used scale in current survey research. When participates answer the questionnaires, they express their degree of agreement.

The format of a typical five-level Likert item, for example, could be as follows:

(a) Strongly disagree;
(b) Disagree;
(c) Neither agree nor disagree;
(d) Agree; and
(e) Strongly agree.

After the questionnaire is completed, each item may be analyzed separately, or in some cases, item responses may be summed to create a score for a group of items. Then to calculate the overall scores according to the participates' selection.

4.5 System Development Tools

We implement the learning path system, automatic learning resource generation system, and student performance evaluation system to demonstrate the validity of our work. To implement them, we have applied a lot of tools of programming languages, Web service, and database. For the learning path system, we use Jgraph, Ext Js, PHP, MySQL, and Apache to implement the prototype. For the automatic learning resources generation system, we use Tomcat, Web Services, and JSP to implement the prototype. And for the student performance evaluation system, we use Excel to analyze data and generate graphs. We briefly introduce how we apply each of them as follows.

4.5.1 Development Tools for Learning Path System

Jgraph

We use Jgraph to design the learning path graphs of the learning path system including its learning activities and the links between the learning activities. Jgraph (www.jgraph.com) is an open resource, Swing compatible graphics component based on MVC architecture and written in the Java programming language. It is the component designed for graphs, which is mainly applied to applications that need to express the graphs structure, such as flow chart, network, and traffic path.

Ext JS

We use Ext JS (http://www.sencha.com/) to design the interface of the learning path system. Ext JS is an AJAX application written in Javascript, which is used to create interactive Web applications rather than the AJAX framework. It can be applied to any application written by Java, .Net, or PHP.

PHP

In this monograph, the editing functions of each learning activity are written by PHP in the learning path system. PHP is a widely used server-side scripting language that is normally used to Web development and can be embedded into HTML. Generally, PHP run on the Web server and generate user-browsed Web pages through running the PHP program. PHP can be deployed on many different servers (Apache, IIS, etc.), operation systems, and platforms (Window, Linux, Unix, etc.) and also can support many database systems, such as MySQL and Oracle.

MySQL
We use MySQL to keep data of learning tasks, learning activities, learning stages, and learning path, and their relationships in the database, so that we can call them when we create/change/delete them. MySQL is a database server, which supports standard SQL and can compile on a number of platforms. It is especially popularly used in Web applications. Especially, phpMyAdmin is the MySQL database system management program written by PHP, which allows administrator manage MySQL database through Web port.

Apache
We use Apache as the local server to run the PHP programs in the learning path system. Apache is a C implementation of HTTP Web server. Apache is the most widely used Web server software, which is an open-source application and can run on all kinds of computer platforms, because of its security and cross-platform. Apache also supports a lot of features, such as server-side programming language support (such as Perl, PHP, and Python) and authentication schemes.

4.5.2 Development Tools for Learning Resources Generation

JSP
We program the learning resource generation system by JSP (Java Server Pages) which is a kind of dynamic Web page technique standard. The aim of JSP is to separate presentation logic from Servlet. JSP embeds Java servlets and JSP tag in the traditional Web page of HTML files and forms the JSP files. The Web application developed by JSP is cross-platform, which can run on different operation systems. JSP is normally executed on the server-side and returns a HTML file to the client-side, so that client-side can browse the file with only a browser.

Tomcat
We use Tomcat to run the JSP program as the Web server for the learning resource generation system. Tomcat is a free open-source Web application server, which provides software applications with services, such as security, data services, transaction support, and load balancing. It is widely used in small system where users are not too many, which is also the best selection for developing and compiling JSP program.

Different from Apache, Tomcat is an extension of Apache, which is a Java implementation of HTTP Web server, and it is actually run JSP pages and Servlet. Tomcat is popularly used because it takes a little system resource when running, has good augmentability, and supports the very common development and application system functions, such as the load balancing and email service.

Web Services
We use Web services to connect our application program and the Web application, so that we can create a Web service from the application. Web services are

application components, which communicate using open protocols. The basic Web service platform is XML plus HTTP. Web service use XML to code and decode data and use open protocols such as SOAP (Service Object Access Protocol) to transport data. Web services can convert applications to Web applications, so that we can publish, find, and use services or provide some functions all over the world through the Web.

4.5.3 Tool for Experimental Results Presentation

Excel We use Microsoft Excel to generate all of these learning progress graphs to evaluate student learning performance. Excel is a spreadsheet application developed by Microsoft. There are plenty of functions can be used to execute computation, analyze information, and manage electronic grid or the data information in the Web pages. It also has very powerful graphic feature. It can display data as line graphs, histograms, charts, and also 3D graphs. Given the statistic data, it can analyze them and dynamically generate intuitive graphs.

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Chapter 5
How to Learn?

Learning Method—Method for Constructing a Fine-Grained Outcome-Based Learning Path Model

Recently, methods have been developed to design learning paths based on attributes that describe learning contents and student characteristics, helping students to learn effectively. A learning path (or curriculum sequence) comprises steps for guiding a student to effectively build up knowledge and skills. Assessment is usually incorporated at each step for evaluating student learning progress. Although existing standards, such as SCORM and IMS-LD, provide data structures to support systematic learning path construction and IMS-LD even includes the concept of learning activity, they do not provide any facilities to help defining the semantics in order for pedagogy to be formulated properly. On the other hand, most existing work on learning path generation is content-based. They only focus on what learning content is to be delivered at each learning path step, and pedagogy is not incorporated. Such a modeling approach limits student learning outcome to be assessed only by the mastery level of learning content, without supporting other forms of assessments, such as generic skills. In this chapter, we propose a fine-grained outcome-based learning path model to allow learning activities and their assessment criteria to be formulated by the Bloom's taxonomy. Therefore, pedagogy can be explicitly defined and reused. Our model also supports the assessment of both subject content and generic skills-related learning outcomes, providing more comprehensive student progress guidance and evaluation.

5.1 Introduction

Learning path defines how a course of study is proceeded. It comprises steps for a student to go through in order to conduct learning. At each step, the student studies certain learning content (i.e., what to learn), which should be disseminated through suitable pedagogy (i.e., learning and teaching approaches). Student assessment should also be included for evaluating student learning progress.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_5

Practically, a student is expected to achieve various learning outcomes, which are broadly categorized into subject-specific knowledge and skills, and generic skills. Specifically, subject-specific knowledge refers to facts and concepts within a subject domain. Subject-specific skill refers to the learning outcome of formulating, evaluating, and synthesizing matters within a subject. Such skill may share among subjects of similar nature. Generic skill refers to the learning outcome that can be applied to various subject domains and student's future development.

Pedagogy formulation and student assessment are main challenges for learning path construction. Considering the practical situations, we use the teaching unit COMP2161 Computer Systems II in our school as an example. We specify "To gain detailed understanding of the difficulties encountered with setting up large computer networks" as a subject-specific knowledge, "To be able to implement and work with different types of computer systems" as a subject-specific skill, and "To be able to communicate technical information in a scientific fashion" as a generic skill, to evaluate part of the student learning outcomes. Subject lecturers are required to design suitable learning activities (i.e., how to learn) helping students to achieve these outcomes, and proper assessment methods to evaluate student learning progress.

In terms of pedagogy, we offer two main types of learning activities: *lecture* and *practical*, where their pedagogies are "learn by perceiving oral presentation" and "learn by experimenting," respectively. Although lecturers can implement more fine-grained pedagogies or even other types, such pedagogies are hard to be formally formulated and reused. In terms of student assessment, defining and assessing subject-specific knowledge is easy, as it is directly tied with the design of teaching subjects. However, subject-specific and generic skills are usually left as written documentation rather than really used for assessing student achievement, since they may require evaluating student learning outcomes achieved from a set of relevant or even all subjects, which is not trivial for implementation.

Existing work on learning path generation for e-learning [Chen08, Kara05, Limo09] is generally content-based without modeling pedagogy or learning activity. Students are usually only assessed by the mastery level of the learning content in each learning path step. As subject-specific and generic skills are dependent on learning activities, therefore, such skills cannot be properly assessed.

SCORM [SCORM] and IMS-LD [IMSLD] are popular standards defining data structures for learning paths. SCORM follows the content-based approach without supporting the assessments of generic skills. Although IMS-LD includes learning activity in their data structure, it only provides a container to hold learning activities without offering any facility to help defining their semantics. As a result, teachers are responsible for manually specifying such definitions, which may be hard to reuse.

In this monograph, we propose a fine-grained outcome-based learning path model for teachers to formulate a course of study as a sequence of learning activities. This allows pedagogy to be explicitly formulated. We also introduce a two-level learning path modeling to facilitate the assessments of different forms of student learning outcomes, including subject-specific knowledge and skills, and generic skills. Our work does not deal with the problem of adaptive learning. Our contributions are as follows:

- **Pedagogical support**: We model a learning activity as a composition of learning tasks enabling teachers to construct the learning and teaching approaches in explicit forms. We also model learning tasks to tie with learning outcomes based upon the Bloom's taxonomy [Bloo56, Krat73, Simp72], such that teachers may be able to formulate comprehensive assessment criteria, as they do in a conventional classroom teaching environments.
- **Student assessment**: We introduce a two-level learning path modeling, allowing teachers to assess collective student learning outcomes generated from individual learning activities or a specific type of learning outcome generated dispersedly from a set of relevant learning activities.
- **Reusability**: Our model allows teachers to reuse their teaching and assessment approaches. It is done by applying a designed learning activity structure to govern the dissemination of another set of learning contents. Given that we formulate pedagogy through a mathematical model, the weight associated with each learning task becomes an intuitive manipulator for teachers to adjust their teaching and assessment approaches for the new learning activity.

We propose a fine-grained outcome-based learning path model. The model is defined mathematically such that the setting of pedagogy and student learning outcome assessment can be explicitly formulated and reused. Considering the fact that a learning path has two functionalities, specifying a student learning process and connecting student learning outcomes for evaluating student progress, this chapter defines learning paths with two levels, namely learning activity (LA) and learning task (LT) levels (Sect. 4.3.2), such that student achievement in both LA-specific and different types of learning outcomes can be comprehensively revealed.

5.2 Overview of the Learning Path Model

Existing learning path generation methods are usually content-based. As illustrated in Fig. 5.1a, b, they construct learning paths based on knowledge elements (KEs), which are delivered through lecturing and assessed by question–answering (Q&A). However, pedagogy is generally not included in their methods. Assessment of different forms of learning outcomes, such as generic skills, is also not properly supported. Such deficiencies impose significant restrictions on these methods for modeling how students are being trained or assessed and rely on teachers to work out these by themselves. Such burden partly explains why learning path generation systems are not widely adopted for learning and teaching in practice.

To model the student learning process, we propose using *learning activities* (*LAs*) [Cono05] instead of KEs to form the building blocks of a learning path as

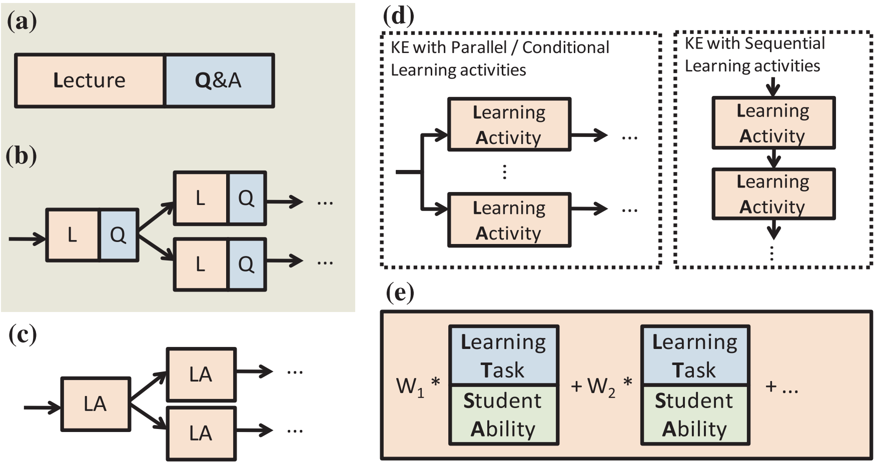

Fig. 5.1 The learning path formulation in existing work and in our work. **a** KE in existing work. **b** Learning path in existing work. **c** Learning path in our work. **d** Example KEs in our work. **e** Learning activity in our work

shown in Fig. 5.1c and model each KE as a set of *LAs*. As shown in Fig. 5.1d, this formulation allows a teacher to govern KE delivery by setting up flow controls to *LAs*, including sequential, parallel, and conditional. The introduction of *LAs* facilitates teachers to define their teaching strategies, i.e., how they disseminate a KE. Learning contents associated with each *LA* can be obtained from the Web or created by teachers.

To support modeling pedagogy of a *LA*, as illustrated in Fig. 5.1e, we define a *LA* to comprise a set of *learning tasks* (*LTs*), where a *LT* is designed to train and assess a specific type of *learning outcome* (*LO*). We associate a weight, w_i (ranging between [0, 1] and $\sum w_i = 1$), to each *LT* indicating its importance in a *LA*, which implicitly defines the amount of time spending on the learning task and the weighting of its assessment. Pedagogy of a *LA* can be adjusted by changing LTs and their weights.

To model *LO* requirement of a *LA*, each *LT* in the *LA* is required to assign with a *SA* as the assessment criteria. Note that two different *LTs* are not restricted to be assessed by different types of LOs. The student learning outcome from a *LA* is then defined as a weighted composition of the *SAs*. With the two-level learning path modeling, student assessment can be conducted at each *LA* or by a specific learning outcome. The *LA*-level learning path helps assessing student learning progress made from a series of *LAs*, while a *LT*-level learning path connects corresponding *LTs* from relevant *LAs* to help evaluating student learning outcomes or skill-specific learning progress.

To support time management in the learning process, we also divide the time span of a *LA*-level learning path into a finite sequence of time slots and refer to each time slot as a *learning stage* (*LS*), where a *LA* may be taken place in a

Table 5.1 Definition of major elements

Abbr.	Key element	Definition
SA	Student ability	Set of attributes indicates how a student makes progress in learning
LT	Learning task	A fine-grained type of training helps a student achieve a specific ability
LA	Learning activity	A training unit comprises a set of LTs to define its teaching and learning approach
LA^C	Collaborative learning activity	A specific type of LA designed for students to learn under a group setting
LP	Learning path	Sequence of steps for a student to go through and build up knowledge and skills
LS	Learning stage	Finite period of time defined within the time span of a learning path

designed *LS* or span over a number of *LSs*. Based on this definition of *LS*, we define a student's *learning progress* as the accumulated learning outcome over some consecutive *LSs*.

In contrast to [Cono05], our model explicitly defines the relationship among learning tasks, formulates their assessments by Bloom's taxonomy, and defines how such assessments are combined to form the learning outcome of a learning activity. We also uniquely support student learning outcome-specific assessment across a series of learning activities. Table 5.1 summarizes the major elements of our learning path model. We will elaborate their details in the following subsections.

5.3 Formal Definitions

Student Learning Outcome: *Student learning outcome* refers to a set of attributes describing whether a student has acquired them after studying something. These attributes may indicate whether the student can only recall the subject content or may apply subject knowledge to solve problems in unseen situations, for instance. In practice, it is a popular approach to assess learning outcomes as a composition of different levels of learning outcomes. For example, a teacher may set different types of question in an examination paper to assess different learning outcomes. Research on learning outcomes was first conducted systemically by a group of educators led by Bloom [Bloo56]. They produced the Bloom's taxonomy to classify thinking behaviors to six cognitive levels of complexity. This taxonomy has been extended to cover three domains: *cognitive* (knowledge based), *affective* (attitudinal based) [Krat73], and *psychomotor* (skills based) [Simp72]. It forms a comprehensive checklist guiding a teacher to ensure that a course design can help training up students with all necessary abilities. Table 5.2 summarizes the Bloom's taxonomy by listing the main characteristics of different learning outcomes

Table 5.2 A summary of the Bloom's taxonomy

Level of complexity	Cognitive (knowledge)	Affective (attitude)	Psychomotor (skill)
1	Knowledge	Receiving	Imitation
2	Comprehension	Responding	Manipulation
3	Application	Valuing	Precision
4	Analysis	Organizing	Articulation
5	Synthesis	Characterizing by value or value concept	Naturalization
6	Evaluation		

according to the Bloom's domains (columns) and their corresponding levels of complexity (rows).

To help formulating the assessment criteria of student learning, we propose using student outcomes from the Bloom's taxonomy as the basis for assessment since they can comprehensively quantify the levels and the types of student achievement. To define the criteria, a teacher needs to identify a set of student learning outcomes used for assessment and puts them into a *Student Learning Outcomes Table* (*SLOT*), which is defined as follows:

$$\text{SLOT} = \left\{A_1, \ldots, A_2, \ldots, A_{|\text{SLOT}|}\right\} \quad \text{for } 1 \leq i \leq |\text{SLOT}| \tag{5.1}$$

where A_i refers to a specific kind of student learning outcome and $|SLOT|$ is the cardinality of *SLOT*. To facilitate the learning outcome assessment, for each learning outcome, two Bloom's taxonomy-related functions $B_c(A_i)$ and $B_d(A_i)$ are set up for retrieving the *level of complexity* and the *Bloom's taxonomy domain*, respectively. For example, the learning outcome of "comprehension" has the complexity level of 2 in the "cognitive" domain, i.e., $B_c(A_i) = 2$ and $B_d(A_i) = \text{Cognitive}$. To gain a better idea on how a suitable set of learning outcomes can be defined in terms of $B_c(A_i)$ and $B_d(A_i)$, the reader may refer to the Bloom's taxonomy [Bloo56, Krat73] or some quick references available on the Web, such as [Bloom].

Although Bloom's taxonomy covers a comprehensive list of learning outcomes, which can maximize the benefits of our model, we expect that some teachers may prefer using a simpler learning outcome model or even define their own lists. This will not affect any functionality of our model. In this sense, new versions of the Bloom's taxonomy are also applicable to our model.

Learning Task: To allow a fine-grained formulation of the learning process of KEs, we introduce the idea of *learning task*, which is designed for training up a student with an outcome-specific learning outcome. By putting together a set of learning tasks, a *learning activity* is formed. Similar to the selection of learning outcomes, a teacher also sets up a *learning task table* (*LTT*), which comprises a list of learning tasks for constructing learning activities as follows:

$$\text{LTT} = \left\{T_1, \ldots, T_i, \ldots, T_{|\text{LTT}|}\right\} \quad \text{for } 1 \leq i \leq |\text{LTT}| \tag{5.2}$$

where T_i is a learning task and $|LTT|$ is the cardinality of *LTT*. A function $S_a(T_i)$ is associated with each learning task T_i to return a student's level of achievement.

Table 5.3 Examples of learning tasks

Type of knowledge	Learning task	Student learning outcomes for assessment	Bloom's taxonomy correspondence
Declarative	Reading	Memorization	Cognitive, level 1
	In-class quiz	Understanding	Cognitive, level 2
	Peer-teaching	Understanding	Cognitive, level 2
Functioning	Case presentation	Understanding	Cognitive, level 2
	Performing a case	Application	Cognitive, level 3
	Computer program design	Synthesis	Cognitive, level 5

The mapping from *LTT* to *SLOT* is subjective; i.e., a teacher can design different types of learning tasks to train up students with the same type of learning outcome.

The design of learning tasks is typically course dependent. As we do not expect teachers having comprehensive knowledge in the Bloom's taxonomy due to its complexity, to help teachers to proceed with the design systematically and in an easier way, we suggest that a teacher may optionally consider whether a learning task is set up for teaching declarative or functioning knowledge [Bigg07]. Declarative knowledge relates to the study of factual information, while functioning knowledge relates to the study of how something works. For example, to design learning tasks for teaching declarative knowledge, reading can be included to help assessing learning outcome in memorization, while an in-class quiz can be set out to assess student understanding. Table 5.3 shows some sample learning tasks along with the corresponding types of knowledge, learning outcomes for assessment, and the Bloom's domains and levels of complexity.

Learning Activity: When designing a course, a teacher typically establishes a set of *learning activities*, such as lecture, tutorial, or practical, for students to learn KEs through different ways. In our formulation, a *learning activity* (*LA*) is formed by a row vector of learning tasks, $\left[T_1, \ldots, T_i, \ldots, T_{|\mathrm{LA}|}\right]$, such that:

$$\mathrm{LA} = \left[w_1, \ldots w_i, \ldots, w_{|\mathrm{LA}|}\right] \left[T_1, \ldots, T_i, \ldots, T_{|\mathrm{LA}|}\right]^{\mathrm{T}} \quad \text{for } 1 \le i \le |\mathrm{LA}| \tag{5.3}$$

where $[\cdot]^{\mathrm{T}}$ is a transpose function, w_i is a weight to indicate the importance of learning task T_i, $\sum w_i = 1$, and $|LA|$ is the cardinality of *LA*. The weights associated with these learning tasks will be added up to 1 or 100 %, meaning that if the weight of a learning outcome (which is associated with one of the learning tasks) has been increased, the rest of the learning outcomes will be decreased in its contribution to this 100 %, and vice versa. Specifically, if the weight of a learning outcome $\boldsymbol{w}$ has been adjusted to become $\boldsymbol{w'}$, the contribution of the rest of the learning outcomes will become $(\mathbf{1}-\boldsymbol{w'})/(\mathbf{1}-\boldsymbol{w})$. Therefore, the weight of any of the rest of the learning outcomes $\boldsymbol{wr}$ will be adjusted to become $\boldsymbol{wr} \cdot (\mathbf{1}-\boldsymbol{w'})/(\mathbf{1}-\boldsymbol{w})$. The *learning outcome* (*LO*) of a *learning activity* (*LA*) can then be assessed by:

$$\mathrm{LO} = \left[w_1, \ldots, w_i, \ldots, w_{|\mathrm{LA}|}\right] \left[f_1(S_a(T_1)), \ldots f_i(S_a(T_i)), \ldots f_{|\mathrm{LA}|}\left(S_a\left(T_{|\mathrm{LA}|}\right)\right)\right]^{\mathrm{T}} \tag{5.4}$$

where $f_i()$ is a function to evaluate the student's level of achievement in a given learning outcome. The weights used in both (5.3) and (5.4) are the same ones, as the weight associated with a learning task also defines the importance of the associated learning outcome of the learning task. Note that we refer T_i as a symbol representing learning task rather than treating it as a mathematical scalar for computation, although in implementation, T_i may be a scalar for storing the ID of a learning task.

Instead of asking teachers to create new evaluation functions, they may reuse existing ones, such as simple marking (quantitative assessment), grading (qualitative assessment), or performing evaluation through the item response theory [Chen06], if they are applicable to the types of learning outcome. As such, our learning path model can fit different types of assessment methods and inference algorithms, which could be subject-specific or a combination of methods for performance evaluation. Note that within a learning activity, each learning task is typically designed for training students up with a different type of student learning outcome.

In fact, modeling a *LA* is not straightforward. Given that different teachers may adopt different teaching approaches, and different students may have different learning styles, the actual tasks used even in the same type of *LA*, e.g., a lecture, can be very different. Such a difference also appears in certain type of *LA* at different subject disciplines. This suggests that we need a more fine-grained model to formulate *LAs* to cope with practical needs. Therefore, we propose to formulate a *LA* as a set of learning tasks. It offers course designers or teachers a way to properly define teaching approaches for delivering KEs. While a *LT* is an implementation of a low-level teaching technique that focuses on training up and assessing students with certain learning outcome, such as an *informal in-class quiz and feedback*, a *LA* is an implementation of a high-level teaching strategy that course designers or teachers use to approach a KE for training up students with a composition of knowledge and skills.

Our model offers a more accurate modeling of learning activities in terms of learning process and learning outcome requirements. Particularly, we formulate a learning activity as a container of a suitable set of learning tasks, such that it can be easily customized by altering its learning tasks to fit a certain subject discipline or the student's learning characteristics. This feature helps accelerating the process of producing new learning activities from existing ones. It is also critical to our previous work on adaptive course generation [Li10], which applies filtering technique to arrange tailor-made learning content for different students at different learning stages, extending it to further support teaching and learning approach adaptation.

Collaborative Learning Activity: A *collaborative learning activity* (LA^C) is a specific *LA* designed for students to learn together in a group setting. In a normal *LA*, its learning tasks and assessments are designed for an individual student. In contrast, a collaborative learning activity comprises two parts: one for an individual student in the group and the other one for the whole group. They apply to both learning tasks and their assessments. Specifically, this kind of learning activity comprises two types of learning tasks, a single set of collaborative learning tasks ψ_C and multiple sets of individual learning tasks ψ_i for $1 \leq i \ll |S|$, where $|S|$ is the number of students participating in the group. Mathematically, ψ_C and ψ_i are one-dimensional vectors of learning tasks (as Eq. 5.5.1) designed to be performed by a group of students together and by an individual student S_i within the group, respectively. To facilitate the assessment of learning outcomes, Ξ_C and Ξ_i are one-dimensional vectors of weights (as Eq. 5.5.2) used to indicate the importance of learning tasks in ψ_C and ψ_i, respectively. Hence, a collaborative learning activity, LA_i^C, designed for a student S_i is defined as follows:

$$LA_i^C = \begin{bmatrix} \Xi_C \Psi_C^T \\ \Xi_i \Psi_i^T \end{bmatrix} \tag{5.5}$$

$$\Psi_C = \left[T_1^C, \ldots, T_{|C|}^C\right] \quad \text{and} \quad \Psi_i = \left[T_1^i, \ldots, T_{|i|}^i\right] \tag{5.5.1}$$

$$\Xi_C = \left[w_1^C, \ldots, w_{|C|}^C\right] \quad \text{and} \quad \Xi_i = \left[w_1^i, \ldots, w_{|i|}^i\right] \tag{5.5.2}$$

where all elements in both Ξ_C and Ξ_i sum up to 1. $T_1^C, \ldots, T_{|C|}^C$ are the set of learning tasks needed to be completed collaboratively, and $T_1^i, \ldots, T_{|i|}^i$ are the set of learning tasks needed to be completed individually. $w_1^C, \ldots, w_{|C|}^C$ and $w_1^i, \ldots, w_{|i|}^i$ are the corresponding weights of importance for collaborative learning tasks and individual learning tasks, respectively. Mathematically, the definitions of both $\Xi_C \Psi_C^T$ and $\Xi_i \Psi_i^T$ are equivalent to Eq. (5.3), and therefore, the student learning outcome can thus be evaluated by Eq. (5.4) when proper learning outcome evaluation functions are in place. We refer collaborative learning tasks in Eq. (5.5) as symbols rather than treating them as mathematical scalars for computation. From the teacher's perspective, the entire collaborative learning activity in a group setting is represented as follows:

$$\mathrm{LA}^C = \begin{bmatrix} \Xi_C \Psi_C^T \\ \Xi_1 \Psi_1^T \\ \vdots \\ \Xi_{|S|} \Psi_{|S|}^T \end{bmatrix} \tag{5.6}$$

Note that the learning outcome of a student can be evaluated in the same way regardless of whether a collaborative learning activity exists; since collaborative learning activity only introduces certain learning tasks having their assessment results shared by some students, the assessment results collected from such learning tasks can still be processed in the same way as those collected from learning tasks conducted by individual students.

Learning Path: *Learning path* (*LP*) is for specifying a student learning steps and linking student learning outcomes for progress evaluation. We define a *LA* level and a *LT* level of learning paths. The *LA* level of *learning path* (*LP*) is made up of an organized set of learning activities. It is modeled as a directed graph, $LP = (V, E)$, defining the course of study for a student. It also links the learning outcomes of *LAs* to facilitate student learning progress evaluation. Specifically, E is the set of edges, while V is defined as follows:

$$V = \left\{LA_1, \ldots, LA_i, \ldots, LA_{|V|}\right\} \quad \text{for } 1 \leq i \leq |V| \tag{5.7}$$

where LA_i is a learning activity and $|V|$ is the cardinality of V. If two learning activities have a prerequisite relation, they will be connected by an edge in E. Our formulation is backward compatible with KE-based learning path models. Specifically, as illustrated in Fig. 5.1d, we can group relevant *LAs* together with their flow control structures to form a KE, turning our learning path model to become KE based. Therefore, it is possible to integrate existing learning path generation system [Chen08, Kara05, Limo09] with our learning path model. Particularly, as we offer a fine-grained modeling on student assessment, this makes more comprehensive student progress information available and that learning path generation results can be enhanced when student learning progress information is considered [Chen06, Limo09]. On the other hand, a *LT*-level learning path is designed to link certain learning tasks defined in relevant learning activities, where those learning tasks are designed to collectively train up and assess a specific type of learning outcome. In terms of the structure, similar to the *LA* level of learning path, a *LT*-level learning path is also a directed graph, but its elements are *LTs* rather than *LAs*. As an illustration, examples of a *LA* "Computer Organization (LT)" and its *LTs* are shown in Sect. 8.1 of Fig. 8.3a, b, respectively. An example of a *LA* level of learning path is shown in Fig. 8.1. Based on this learning path, two sample *LT*-level learning paths, which assess communication skill and writing skill of a student, respectively, are shown in Figs. 8.5 and 8.6.

Learning Stage: To provide teachers a metric to control the number of learning activities taking place at any period of time and to schedule learning activities properly, we divide the time span of a learning path into a finite sequence of time slots and refer to each time slot as a *learning stage* (*LS*). A learning activity may take place in a designated learning stage or may span over a number of learning stages. The definition of learning stage well matches the timetabling concept well in practice, where a teacher may divide an entire course taking place with a finite sequence of time slots, such as teaching weeks or semesters, and assign a proper number of learning activities to each time slot. During each learning stage, a student only needs to study a subset of KEs through designated learning activities. To indicate the *starting learning stage* (*sLS*) and *ending learning stage* (*eLS*) of a *LA*, we set up two functions, $LS_s()$ and $LS_e()$, respectively, as follows:

$$\mathrm{sLS} = \mathrm{LS}_s(\mathrm{LA}) \tag{5.8}$$

$$\mathrm{eLS} = \mathrm{LS}_e(\mathrm{LA}) \tag{5.9}$$

To govern the student learning process, *time constraints* and *dependencies* are often set up among the learning activities. The time constraint is defined based on the concept of *learning stages*. If two learning activities, LA_j and LA_k, are specified to start at the same learning stage, then they are satisfied with the following constraint:

$$\mathrm{LS}_s\left(\mathrm{LA}_j\right) = \mathrm{LS}_s(\mathrm{LA}_k) \tag{5.10}$$

We may also set up some rules using $LS_s()$ and $LS_e()$ to verify whether LA_j and LA_k overlap each other at some learning stages. These time constraints are useful for verifying the *coexistence dependency* of LA_j and LA_k. We need these rules particularly when we need to make sure that a set of chosen learning activities are conducted in parallel at some point. On the other hand, if LA_j is designed to complete before LA_k starts, then we have:

$$\mathrm{LS}_e\left(\mathrm{LA}_j\right) < \mathrm{LS}_s(\mathrm{LA}_k) \tag{5.11}$$

This time constraint can be applied as a rule to ensure the *prerequisite* relation between LA_j and LA_k.

Student learning progress: Learning progress describes how much knowledge or skill that a student has acquired from a course over certain learning stages. With Eq. (5.4), learning outcome can be evaluated as a weighted composition of learning outcomes achieved from a learning activity. Therefore, student learning progress can be computed as an accumulated learning outcome over certain consecutive learning stages, by following the *LA*-level learning path based on a selected group of *learning activities* for assessing *subject-related outcomes*. Alternatively, we may evaluate a student's learning progress on a specific learning outcome based on a *LT*-level learning path. This allows assessing the *generic outcomes or transferable skills* [Dodr99], which are typically related to personal effectiveness, e.g., communication and teamwork skills. This feature generally cannot be achieved in existing methods as they use KEs to construct learning paths.

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Chapter 6
What to Learn?

Learning Contents—Method for Learning Path Construction Based on Association Link Network

In the last chapter, we mainly formulate learning activities to construct the learning path based on learning outcomes in terms of how to learn. We still need to design learning resources forming the learning contents that are used in a learning path to define what to learn. Manually designing the learning resources is a huge work to teachers and quite time consuming. To solve this problem, we can make use of the Web resources by turning them into well-structured learning resources for students with different knowledge backgrounds and knowledge levels. So the key problem of constructing personalized learning path is to generate learning resources by identifying the knowledge structure and attributes of these Web resources, and to correctly deliver them to students. In this chapter, we show how we construct well-structured learning resources from loosely connected Web resources by constructing a set of three different networks to formulate topics, keywords, and the actual learning resources. Such formulation is used to generate learning paths with different abstractions of knowledge, helping students to better understand the knowledge covered by the learning resources.

Nowadays the Internet virtually serves as a library for people to quickly retrieve information (Web resources) on what they want to learn. Reusing Web resources to form learning resources offers a way for rapid construction of self-paced or even formal courses. This requires identifying suitable Web resources and organizing such resources into proper sequence for delivery. However, getting these done is challenging, as they need to determine a set of Web resource properties, including the relevance, importance, and complexity of Web resources to students as well as the relationships among Web resources, which are not trivial to be done automatically. Particularly each student has different needs. To address the above problems, we present a learning path generation method based on the Association Link Network (ALN), which works out Web resource properties by exploiting the associations among Web resources. Our experiments show that the proposed method can generate high-quality learning paths and help improving student learning.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_6

6.1 Introduction

Learning resources (LRs) refer to materials that help students to learn and understand certain knowledge. Such LRs can be constructed by different types of media, including text, audio, and video. Typically, producing LRs is very time consuming. With the availability of the Internet, such situation may be improved, as information covering a huge variety of ready-made knowledge, namely Web resources, is made available. Examples of Web resources include materials from Wikipedia, BBC, and Reuters. Reusing such resources may help teachers to significantly reduce their time on producing LRs and may also facilitate the generation of self-paced courses. However, Web resources may be loosely connected without any well-defined structure or relationship and may also be redundant. It is not trivial to transform Web resources into LRs, as relationships among LRs are required to be well defined and LRs should be arranged to deliver in a proper order for a particular student to study.

Identifying relevant LRs is essential to learning path generation. Existing works determine such a relevancy by matching student-specific requirements, including topics to learn, learning preferences, or constraints [Farr04, Dolo08] against the characteristics of LRs, which can be maintained by a list of attributes, such as related topic and difficulty level, or additionally by a structure that defines how LRs are related among each other [Meli09]. Learning path generation methods aim at arranging selected LRs into a proper sequence for delivering to students, so that they can learn effectively in terms of minimizing the cognitive workload. Basic work [Farr04] only considers attributes associated with each LR, such as its related topic. More advanced works [Kara05, Chen08] consider the structure among LRs which facilitates them to model the cognitive relationships among LRs. Such relationships are fundamental to learning effectiveness. However, structures among LRs are not trivial to build. Existing work considers using predefined structures [Kara05] or generating LR structures based on pretest results [Chen08], which involves significant human efforts.

In order to assess student learning performance and see whether they could achieve their learning outcomes, we need to evaluate them by tests. Normally, teachers need to manually create tests for students [Huan07]. However, it is quite time consuming and causes a huge work for teachers. And this issue makes it impossible to design personalized tests if teachers have to design questions on their own. [Chen08] prepared a database to store a lot of questions beforehand, so they can generate tests by randomly selecting a set of questions. But it is very expensive to collect a database of questions, and they cannot generate personalized tests for different students. It is necessary to automatically generate tests, in order to make the teaching and learning more intelligent.

We present a learning path (LP) generation method based on the Association Link Network (ALN) [Luo08A, Luo11], which discovers knowledge structure among Web resources based on association. This allows teachers to reuse Web resources forming LRs, where relationships among LRs are automatically constructed. We also proposed an automatic test generation scheme (ATGS), which is constructed based on Association Link Network (ALN). It contains 3 abstraction levels of ALN, i.e., keyword, topic, and learning resource ALN, to show the relationships of learning resources. Our method applies the 3 abstraction levels of ALN to analyze the relations between concepts, and use the relations of learning resources to refine the relations of concepts and make them more precise and specific. Also, the number of keywords and the number of relations with other keywords decide the complexity of a learning resource, so that we can distribute appropriate learning resources to students who have the corresponding knowledge levels. This scheme can provide automatically generated tests for different types of students according to their different knowledge levels. Thus, students can build up their knowledge models through completely learning these knowledge concepts. In order to improve the learning quality, we consider the test as a part of cognitive learning process where learning is guided by the cognitive process.

The main contributions of our research study in this chapter include:

- We apply ALN to transform Web resources into well-structured LRs, where the pedagogical attributes of LRs, including their knowledge domain, importance, and complexity, can be automatically determined. This allows us to construct a teacher knowledge model (TKM) for a course and generate adaptive learning path to each student. We also maintain a student knowledge model (SKM) to monitor student learning progress.
- We model the TKM as well as the LP by 3 ALNs, namely LR, topic, and keyword-based ALNs. This modeling allows students to perceive the relationships among LRs through different abstraction levels, which can help students to minimize their cognitive workload during the learning process.
- We construct an automatic test generation scheme to automatically assess student understanding against a LR within a UoL. We use the associations between topics or keywords as the rules to test whether students can build up correct associations between major concepts, and we distribute LRs with different complexities to students with different knowledge levels. This automatic scheme saves a lot of efforts to manually design tests.
- We use cognitive theory of learning, which contains three phases, to control student learning process, where the test is considered as one of the phases. In the process of learning, students are required to complete the learning of a knowledge element through repeating the three phases. So learning quality is controlled by the cognitive learning process.

6.2 The Teacher Knowledge Model

The Association Link Network (ALN) [Luo08A, Luo11] is designed to automatically establish relations among Web resources, which may be loosely connected without well-defined relations. ALN defines relations among Web resources by analyzing the keywords contained in Web resources. Such relations are referred as associations, which link up Web resources and ALN to describe the semantic relationships of Web resources, and turn Web resources into LRs. In our work, we further exploit such associations to automatically formulate some key attributes of LRs, including their importance and complexity, which are the fundamentals to LP generation. The LPs comprise a set of sub-ALNs, which are parts of the whole set of ALNs, respectively, namely LR, topic, and keyword, to help students to perceive LRs together with their multiple levels of relationships. By following such learning paths, the cognitive workload of the student on learning can be greatly reduced. To set up a measure for evaluating student learning progress, we define the set of ALNs that link up all available LRs of a course as the teacher knowledge model (TKM). We also maintain a student knowledge model (SKM) (Ref. Sect. 6.3) to describe student learning progress. SKM comprises the system recommended LP and the part of the LP that a student has finished studying, together with all relevant LRs. SKM also comprises a student profile, indicating the student's knowledge levels and preferred topics.

Technically, the foundation of ALN is the association of keywords, where there exists an association link between two keywords appear in the same paragraph. To facilitate the formulation of LRs and the learning paths, we extract the most important keywords identified from a set of LRs as topics, where the association link between two topics is inherited from that between the corresponding keywords. The topics are used as a means to determine whether any two knowledge concepts are related. In contrast to a topic, a keyword only indicates a certain aspect of a piece of knowledge concept. On the other hand, there exists an association link between two LRs if some keywords contained in the two LRs are associated with each other. As an ALN represents the network of a set of nodes $\{c_1, c_2, \cdots, c_n\}$ by their association, where n is the number of nodes. Mathematically, an ALN is represented by a matrix of association weights aw_{mn} , where each formulates the association relation between a cause node c_m and an effect node c_n. It is defined as in Eq. 6.1:

$$ALN = \begin{pmatrix} aw_{11} & \dots & aw_{1n} \\ \vdots & \ddots & \vdots \\ aw_{m1} & \dots & aw_{mn} \end{pmatrix} \tag{6.1}$$

Particularly, LRs, topics, and keywords are all modeled by ALNs. An ALN can be automatically and incrementally constructed by adding or removing nodes. When a new node is added to an ALN, we need to check such a node against all existing nodes in the ALN, identifying whether the nodes are relevant and computing the association weights between the newly added node and each of the relevant existing nodes in the ALN. When removing a node, all association links induced by the node will be removed. This incremental property makes adding new Web resources to form new LRs or removing LRs to form a course easily. We now depict the details of the construction of the three different ALNs in our system.

To turn a set of Web resources into learning resources, we initially extract their keywords and construct the association links among the keywords by Eq. 6.2.

$$aw_{ij} = P(k_j|k_i) = \sum_{k=1}^{n} b_{ir}/n \tag{6.2}$$

where aw_{ij} is the association weight from cause keyword k_i to effect keyword k_j, k_i is associated with k_j when they exist in the same paragraph p_m [Luo08A]. An association weight, which is also the $P(k_j|k_i)$, indicates the probability that the occurrence of cause keyword k_i leads to effect keyword k_j in the same paragraph at the same time. b_{ir} is the probability that the occurrence of cause keyword k_i in the rth sentence leads to the occurrence of effect keyword k_j in the same sentence. n is the number of sentences in the paragraph p_m. We apply TFIDF Direct Document Frequency of Domain (TDDF) [Luo08B] to extract domain keywords from a set of Web resources, where keywords are texts that appear in a good number of Web resources; i.e., the document frequency is higher than a threshold. The associated relation is determined by $A \xrightarrow{\alpha} B$, meaning that if node A is chosen from an ALN, node B will also be chosen with the probability α.

We then extract and link up topics from the LRs. Topics refer to the most important keywords, which have the highest numbers of association links than the other keywords, meaning that they can represent the most important information of a set of LRs. In our experiments, we select the top 20 % of keywords forming the topics. Pedagogically, topics model the knowledge concepts covered by the LRs, while keywords are associated with a topic as the topic's key attributes, which help explaining why certain knowledge concepts are related to some others. This modeling is much comprehensive than existing work, as they only associate LRs based on topics.

To construct LRs for a course, we follow the knowledge domain (i.e., a set of topics) of the course and select relevant Web resources that match the knowledge domain, turning such resources into LRs. We have conducted experiments on our method using 1085 Web resources about health information from www.reuters.com/news/health. We do not create LRs for similar Web resources in order to avoid students' spending time on learning similar contents repeatedly. We check Web resource similarity based on their keywords and association links. In the implementation, we pick the first selected item of such Web resources to create a LR and stop creating further LRs for any Web resource that has a high similarity. Figure 6.1 shows part of the keyword ALN that we have created, where each node represents a keyword, and each edge, namely an association link, represents the existence of an association between two nodes. Actually, in Fig. 6.1, each edge has its value of association weight in the matrix of ALN, indicating the association degree between the two keywords that are connected by the edge. The importance of a node is directly proportional to the number of association links connecting to it. Note that the edges showing in the figure do not imply any association weight.

TKM formulates the overall knowledge structure of a course based on topic, keyword, and LR ALNs. Research [Shaw10] shows that formulating concepts into a knowledge map, which is a graph having concepts as nodes and they are connected by links that model the relationships between two concepts, can significantly improve student understanding, particularly when comparing with studying

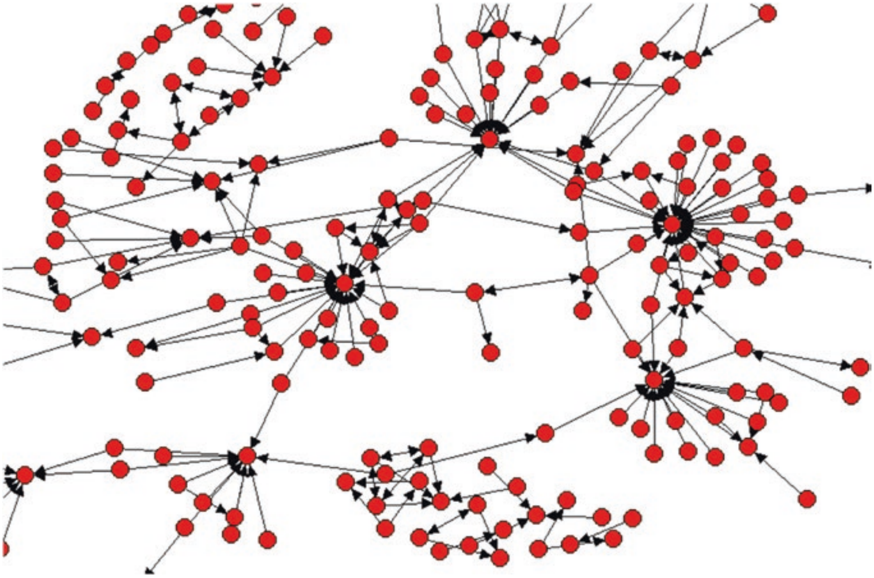

Fig. 6.1 An illustration of a keyword-based ALN

through LRs collated by a simple Webpage browse-based structure. Our ALN-based knowledge structure is similar to a knowledge map. Instead of having free-style labeling to formulate the relationship (i.e., the link) between two concepts, we use association weight to model quantifiable relationships among concepts. In addition, we have three different types of ALNs representing different abstraction levels of a set of concepts, i.e., topic, keyword, and LR ALNs, where the relationships among such ALNs are also explicitly defined, i.e., given a node in an ALN, the corresponding nodes in the other two ALNs are well defined. This implies that it is easy to retrieve LRs based on student-preferred topics and the knowledge structure for a set of LRs.

The ALN structure also allows us to automatically compute the complexity and the importance of each LR, avoiding instructors or course designers to manually define such attributes, which is extremely time consuming when there are a massive number of LRs to deal with. More specifically:

- We compute the complexity of a LR, which can be used to match student knowledge level, based on the algebraic complexity of human cognition that associates with the complexity of both keywords and association links of the LR X as in Eq. 6.3.

$$\lambda_X^T = \sum_{K=0}^{D-1} W_k \cdot \lambda_X^k \tag{6.3}$$

where λ_X^T is the text complexity of LR X in terms of keywords, D is the number of keywords in LR X. λ_X^k is the number of degree-k association, i.e., the number of keywords having k association links connected to LR X, which indicates the complexity of association link. W_k is the number of keywords having degree-k association, which indicates the complexity of keywords. A LR is low in complexity if it has low number of association links while such links are of low degrees.

- The number of association links indicates the number of relationships existing between a node and its connected nodes. The association weight indicates how strong a node is related to another one. We therefore use the association weight and the number of association links to indicate the importance of a node.

6.3 Student Knowledge Model and Personalized Learning Path

Student knowledge model (SKM) formulates student learning progress. It comprises a dynamically generated personalized LP and a set of student characteristics. A personalized LP is technically a subset of the TKM. Student characteristics that we have considered include knowledge background, knowledge level, and preferred knowledge concepts, which are learned topics, learning performance on such learned topics, and topics that a student is interested or can effectively learn, respectively. The algorithm for personalized LP generation is as follows:

(1) **Initialization**: Based on the topic ALN of TKM, we determine the starting point of a personalized LP according to the initial knowledge of a student, i.e., the topics learned. If such information does not exist, we consider the topics, where their complexity matches the student's knowledge level, and select the most important one as the starting point. This ensures the most suitable and fundamental knowledge is selected for a student to start learning. We compute the complexity of a topic by considering the average complexity of all LRs associated with the topic as follows:

$$D_T(x) = \frac{1}{N} \sum_{p=1}^{N} \lambda^T \left(LR_p\right) \tag{6.4}$$

where $D_T(x)$ represents the complexity of topic x, and $\lambda^T\left(LR_p\right)\left(LR_p\right)$ is the complexity of LR p (ref. Eq. 6.3).

(2) **Incremental LP Generation**: Based on the current node of a LP, we incrementally generate the next node of the LP by identifying a suitable one from the set of direct connected nodes according to the topic ALN of TKM. The selection is based on two criteria: the *complexity* and the *importance* of the topic. The complexity of the topic should match the student's knowledge

level. If there are more than one node meeting the complexity criteria, we then select the node with the highest importance $I_{S_i}(x)$, which is formulated by the summation of association weights where student preference on a topic is considered as in Eq. 6.5:

$$I_{S_i}(x) = \sum_{j=1}^{n} aw_{xj}(x).P_{S_i}(x) \tag{6.5}$$

where I_{S_i} represents the importance of topic x for student i, $aw_{xj}(x)$ represents the association weight between topic x and topic j, and $P_{S_i}(x)$ represents student i's degree of preference on topic x, which could be any value from 0 to 1, and "0" indicates no preference and "1" indicates full preference.

(3) **LR Selection**: Based on the LR ALN of TKM, we select a set of LRs, where their associated topics match with the selected topic by step 2. As shown in Eqs. 6.6 and 6.7, a student-specific LR p will be identified by matching the complexity $\lambda^T\left(LR_p\right)$ of the LR with the knowledge level KL_{S_i} of the student. We use the coefficient 0.1 to constrain the error between the complexity of LRs and the student's knowledge level, where the error should be smaller than a tenth of the students' knowledge level. We can recommend LRs that best fit the student's knowledge level.

$$LRs = \left\{p \middle| \left\| \lambda^T\left(LR_p\right) - KL_{S_i} \right\| < 0.1KL_{S_i}\right\} \tag{6.6}$$

$$D_{S_i}(x) = \lambda^T\left(LR_p\right)/P_{S_i}(x) \tag{6.7}$$

LP Progression and Alternative LP: After a student successfully studying a LR, we update the SKM by indicating the student has finished such a LR and the associated keywords. Our system will then go back to step 2 again for incremental LP generation. If a student fails the corresponding assessment, it is likely that the student lacks the knowledge of some aspects of the topic about the LR. To deal with such a learning problem, we adjust the LP by redirecting the student to learn an alternative LR, which is the most important unlearned prerequisite node of the failed LR as defined in the LR ALN of the TKM, before coming back to learn the failed LR. Such an alternation may be carried out repeatedly on the rest of the unlearned prerequisite node of the failed LR if necessary. Figure 6.2 gives an example of a recommended learning resources by the system.

(4) **Learning Performance**: A student i has finished learning a course when there is no more LR to follow. Student learning performance D_i can be computed by the difference between the real performance SKM_i (i.e., the finished LP) and the expected performance LP_i defined by the recommended LP as stored in the TKM:

$$D_i = \|SKM_i - LP_i\| \tag{6.8}$$

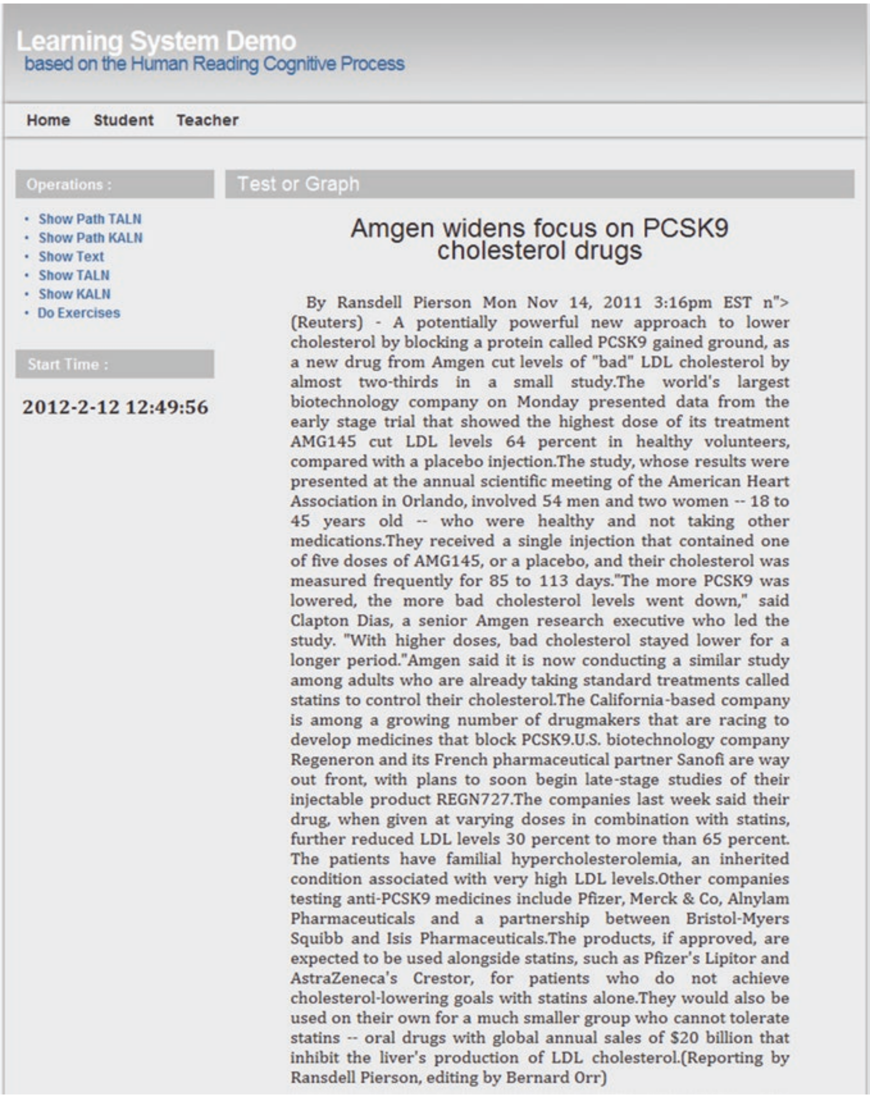

Fig. 6.2 Example of a recommended learning resource

where D_i evaluates whether the student has a good learning performance at the end of the student's learning. The student has a better learning performance if SKM_i is closer to LP_i. Figure 6.3 shows an example of a system recommended LP formed by a set of the three abstraction levels of ALNs for a student. Figure 6.3a depicts the topic ALN that comprises 5 topics, forming the topic level of the LP (i.e., project → president → lead → plastic → pharmacy), where the edge thickness indicates the association weight. The path

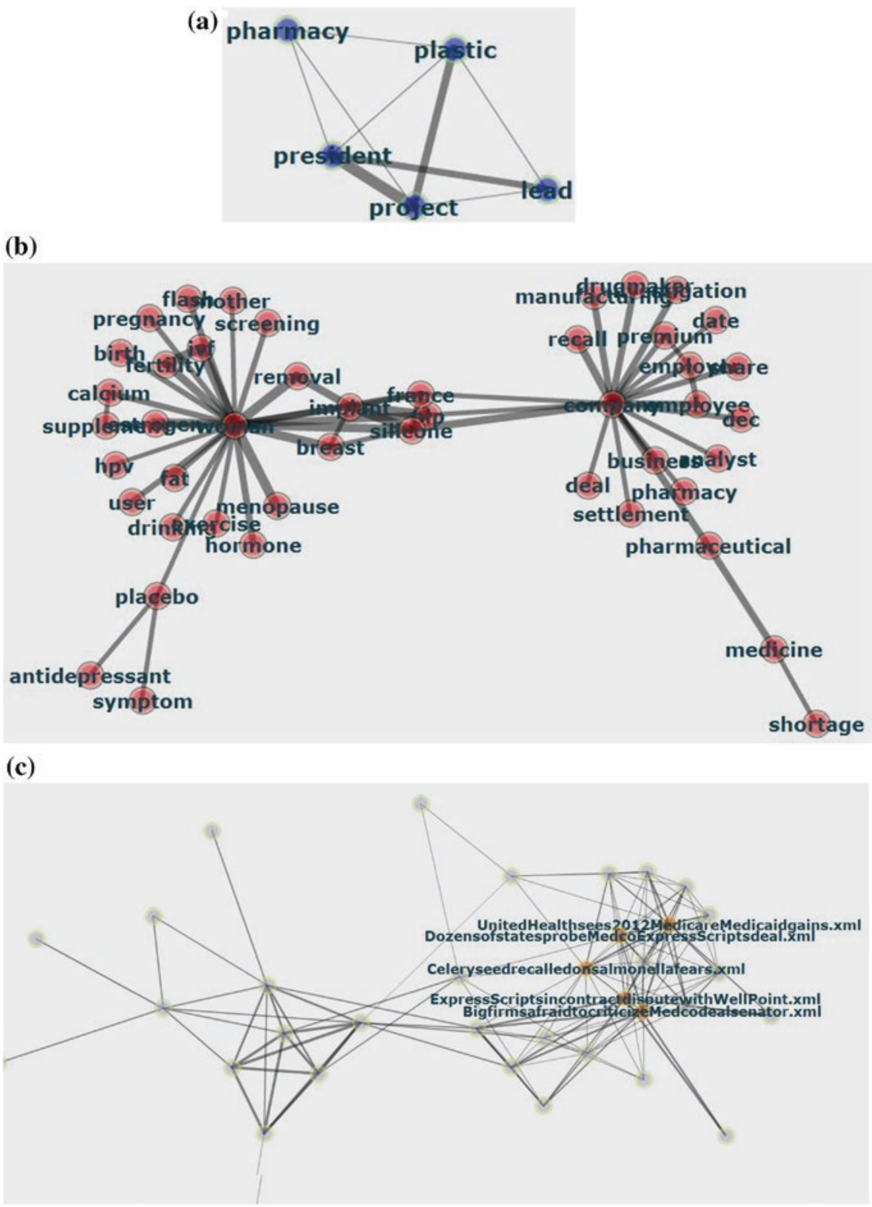

Fig. 6.3 System recommended learning path in 3-ALN. **a** The path automatically selected by system. **b** The correspondence keyword ALN. **c** The correspondence learning resource ALN and selected learning path of learning resources for students

starts from the most important topic "project," and then the second important one which has to connect with the first one is "president," and end with the least important one "pharmacy." All keywords that have association with the five topics are extracted from the teacher knowledge model of keyword abstraction level, together with their association links in between to form the learning path in keyword abstraction level, as shown in Fig. 6.3b. And all LRs that contain the five topics are extracted from the teacher knowledge model of LR abstraction level as well, together with the association links in between to form the learning path in the LR abstraction level, as shown in Fig. 6.3c. However, students may not have enough time to learn all these LRs, so we just recommend them the LRs that match with the student's knowledge level. The highlighted LRs as shown in Fig. 6.3c are the recommended LRs that match the student's knowledge level. Since there are associations among LRs through sharing keywords, a student showing interest in a LR may also interest in its associated LR. A student can also gain understanding in a LR through its associated LRs. Our three different ALNs provide such associations and therefore help improving student learning.

6.4 Student Assessment Against Learning Resources

In our method, student assessment is embedded into the learning process of each learning resource, allowing us to determine whether a student has completed learning a certain piece of knowledge with a proper level of understanding. The assessment result provides a means for updating student profiles regarding students' knowledge levels and completed knowledge concepts.

Cognitive Process

In fact, learning process is a cognitive process of knowledge and behavior acquisition, which is commonly perceived as a process of association of a certain form of new concepts with existing knowledge in the memory of the brain. So in our monograph, as a part of the learning process, the assessment is also designed to follow the cognitive process. In cognitive science, learning is deemed as a relatively permanent change in the behavior, thought, and feelings as a consequence of prior learning experience. So we need to assess students' prior learning experience to see whether they have made a relatively permanent change. In our monograph, both learning process and assessment construct the whole cognitive process. According to Learning Intelligent Distributed Agent (LIDA) cognitive cycle [Fran06] which is designed based on the theory of human cognitive cycle, students should go through the cognitive cycle to complete the cognitive process of learning knowledge. In the cognitive cycle, students carry out their learning in 3 states, namely understanding state, attention (consciousness) state, and action selection and learning state. We use a set of three different ALNs to help students to complete the cognitive process.

Automatic Test Generation Scheme and Implementations

The keyword ALN presents the associations among domain keywords from a set of Web resources, where keywords are texts that appear in a good number of Web resources, i.e., the document frequency is higher than a threshold. The topic ALN are extracted from the keyword ALN, which presents the associations among the most important keywords, which have the highest numbers of association links than the other keywords, meaning that they can represent the most important information of a set of LRs. To construct LRs ALN, we follow the knowledge domain (i.e., a set of topics) of the course and select relevant Web resources that match the knowledge domain, turning such resources into LRs.

By considering the example of a learning resource as shown in Fig. 6.2, we explain how the three states control the studying of a learning resource within the cognitive cycle by Figs. 6.4 and 6.5. In the understanding state, we highlight the major attributes (keyword ALN, Fig. 6.4a) and knowledge concepts (topic ALN, Fig. 6.4b) of the learning resource to help students to focus on the important aspects of the learning resource. In the attention state, we present the associations among different topics and keywords by the links of keyword ALN and topic ALN. We are not requiring students to memorize the networks, but helping them understand the knowledge structure and the related aspects of a knowledge concept. The nodes in Fig. 6.4 represent the major attributes and knowledge concepts, the links between nodes represent the associations among them, and the colors are just randomly assigned to the nodes to distinguish overlapped nodes in case the nodes are too many. "Pharmacy" is related to "plastic," while "statin" is not related to "cholesterol." It means when "pharmacy" appears in a sentence, it often comes with "plastic." Although "statin" may be related to "cholesterol," but in this LR, when "statin" appears in a sentence, it does not come with "cholesterol." In the action state, we assess students if they can build up correct associations of the major attributes or the knowledge concepts using the automatically generated test as shown in Fig. 6.5 where we ask students to choose the correct associations between keywords or topics from the choice questions. Because the tests are generated by determining whether two major attributes or knowledge concepts are related to each other, we are able to determine whether students can understand the LR. However, there is no need to straightly carry out the three states one after another. Students can jump to any state during the process. If they got failed in the test, they can jump to the other state to learn again and then go back to a new test until they understand the knowledge. To evaluate student learning performance, we automatically generate tests using a test generation schema by the following steps:

- Step 1: Select an association link from the topic ALN (for example, Fig. 6.4a or the keyword ALN (for example, Fig. 6.4b);
- Step 2: Determine the complexity of the selected association link λ_X^k which has been introduced in Sect. 6.2 as the difficulty of level of the question;

The ALN structure allows us to automatically compute the complexity of each piece of LR, avoiding instructors or course designers to manually define such

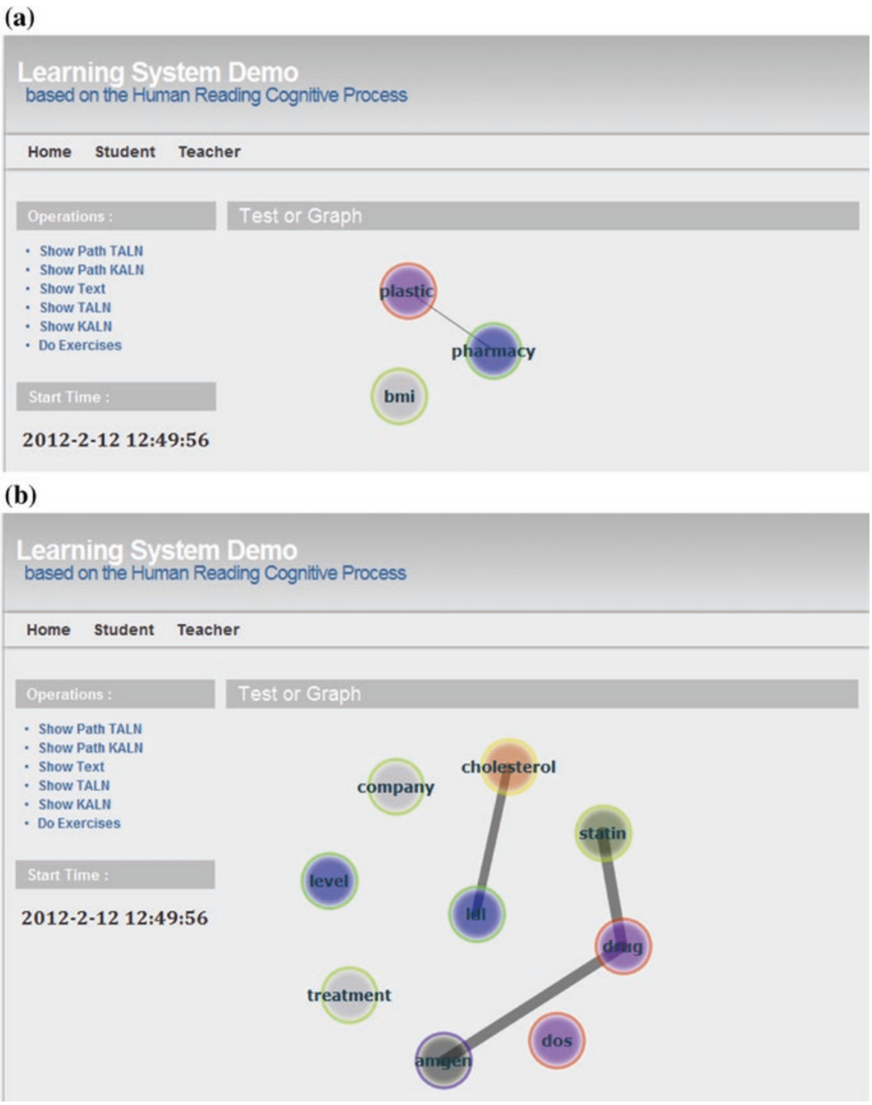

Fig. 6.4 State understanding and attention: highlight the major attributes; build up associations among topics and keywords. **a** Topic layer of ALN that exists in the learning resource. **b** Keyword layer of ALN that exists in the learning resource

attributes, which is extremely time consuming when there are a massive number of LRs to deal with. We compute the complexity of a LR, which can be used to match student knowledge level, based on the algebraic complexity of human cognition that associates with the complexity of both keywords and association links of the LR X as Eq. 6.9.

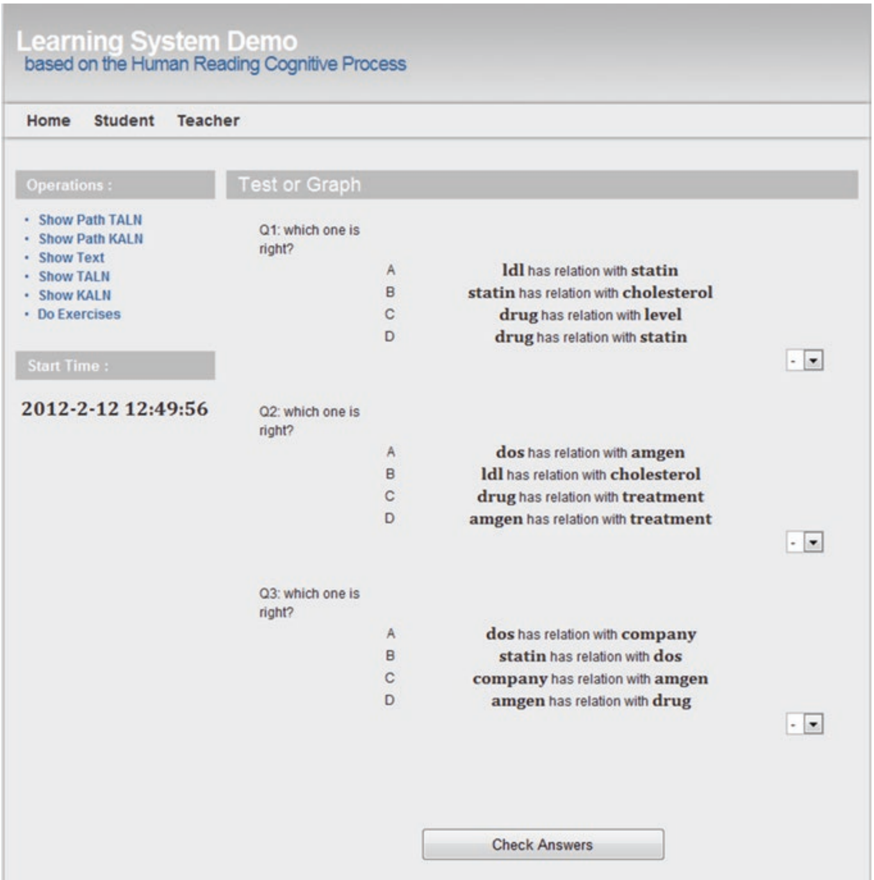

Fig. 6.5 An example of automatic generated test

$$\lambda_X^k = \sum_{K=0}^{D-1} W_k.\lambda_X^k \tag{6.9}$$

where λ_X^k is the text complexity of LR X in terms of keywords, D is the number of keywords in LR X.λ_X^k is the number of degree-k association, i.e., the number of keywords having k association links connected to LR X, which indicates the complexity of association link. W_k is the number of keywords having degree-k association, which indicates the complexity of keywords. A LR is low in complexity if it has low number of association links while such links are of low degrees.

- Step 3: Add natural languages in between to bridge the associated two keywords into a new sentence as the corrected option of the question;

- Step 4: Randomly select any two keywords which have no association in between, and also add natural languages in between to bridge the associated two keywords into a new sentence as the distracted options.

In this way, tests (for example, Fig. 6.5) can be automatically generated without any manual effort. We can save a lot of time for teachers. In the test, all questions are presented in the way of choice-question with four options, and each option describes whether two keywords have associations in between. A student selects the correct option from them. This test generation schema can be applied to any learning resource, which can automatically generate different levels of questions and help students to strengthen their understanding. So it is easy to control the difficulty levels of the tests for assessing different students. In the end, each student's errors have different distribution over the TKM. If the errors concentrate on a small area, then the student has problems on related topics, so the student just needs to pay a few efforts to get improved. However, if the errors distribute over the network, then the student has problems on many different topics, so the student needs to pay huge efforts to get improved.

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Chapter 7
How to Improve Learning Quality?

Method for Fuzzy Cognitive Map-based Student Progress Indicators

Learning path shows students what to learn and how to learn, but we still need to evaluate student learning performance and check their learning quality. This learning progress information can help teachers to improve their teaching approaches and let students know whether they are on the right track of progress. As there are a lot of attributes that can affect student learning quality, we have developed a method to identify the attributes that may affect a certain type of students a lot or a little and present students how their learning progress changes with these attributes.

Student learning progress is critical for determining proper learning materials and their dissemination schedules in an e-learning system. However, the existing work usually identifies student learning progress by scoring subject-specific attributes or by determining status about task completion, which is too simple to suggest how teaching and learning approaches can be adjusted for improving student learning performance. To address this, we propose a set of student learning progress indicators based on the Fuzzy Cognitive Map to comprehensively describe student learning progress on various aspects together with their causal relationships. These indicators are built on top of a student attribute matrix that models both performance and non-performance-based student attributes, and a progress potentiality function that evaluates student achievement and development of such attributes. We have illustrated our method by using real academic performance data collected from 60 high-school students. Experimental results show that our work can offer both teachers and students a better understanding on student learning progress.

7.1 Introduction

Both teaching and learning become flexible and adaptive. Teachers often need to provide students various feedbacks, including scores and breakdowns, description on what went good/wrong, and suggestions for further improvement. Most

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_7

of this information can be expressed numerically and consolidated to form inputs to the e-learning systems [Li08] for generating adaptive courses. They may also form meaningful feedbacks to help teachers and students to make various enhancements. However, the existing work has not been exploited such information well. This chapter addresses this issue. We present a student progress-monitoring model which forms a core component of e-learning systems. Our model aims to generate comprehensive feedback indicators which allow students to understand their learning performance and how they can be improved, allow teachers to adjust their teaching approaches based on student learning performance, and allow both parties to identify the main parameters to affect student learning progress and their developments in different attributes. Our model was based on the students' performance-related attributes (PAs) as well as non-performance-related attributes (NPAs) to model student learning performance and their potentialities to make progress. We also infer the causal relationships among these attributes to reflect how they affect the changes of one another. They are useful to making teaching approaches to different groups of students. Hence, our work contributes to the development of adaptive e-learning technologies. The main contributions are as follows:

- Proposing student attribute descriptors to mathematically model the casual relationship and the changes of both performance- and non-performance-based attributes of students. This sets the foundation to support student learning progress analysis.
- Proposing student learning progress indicators to pedagogically depict student learning progress and development in terms of individual student and various groupings, and against teacher's expectations.

7.2 Mathematical Model

Analyzing student learning progress is not trivial. Different subjects (or learning activities (*LAs*) [Yang10]) have different assessment criteria, where some are subject-specific, but some are shared among subjects. On the other hand, student learning styles and learning modes also play significant roles on how a student perform and make development in different assessment criteria. We have developed the student attribute descriptors to provide a more complete picture on student learning progress and development.

7.2.1 Modeling of Student Attribute Descriptors

Student Attribute Matrix

We propose a student attribute model (SAM) (Eqs. 7.1 and 7.2) to incorporate both performance (PA)- and non-performance (NPA)-based learning attributes,

Table 7.1 Attributes from Bloom's taxonomy

Level of complexity	Cognitive (knowledge)	Affective (attitude)	Psychomotor (skill)
1	Knowledge	Receiving	Perception
2	Comprehension	Responding	Mind set
3	Application	Valuing	Guided response
4	Analysis	Organizing	Mechanism
5	Synthesis	Characterizing by value or value concept	Complex overt response
6	Evaluation	/	Adaptation
7	/	/	Origination

Table 7.2 Attributes regarding learning styles and learning modes

Learning mode	Perception	Input	Organization	Processing	Understanding
Collaborative	Concrete	Visual	Inductive	Active	Sequential
Individual	Abstract	Verbal	Deductive	Reflective	Global

forming an unified representation to support student learning progress and development analysis. SAM is the foundation of student attribute descriptors. It comprises subject-related and generic outcome attributes from Bloom's taxonomy [Bloo56] (Table 7.1), learning style attributes from Felder-Silverman's model [Feld88], and learning mode attributes describing whether a learning activity is an individual or a collaborative one [Gokh95] (Table 7.2). We apply a different version of Bloom's taxonomy from the version we applied in Chap. 4, which categorizes the Psychomotor domains into 7 levels rather than 5 levels. Because we found that this way to divide Psychomotor domains is much more easier to be understood by teachers and students in the user study. We have adopted these well-established models to describe student attributes as they have been widely used and verified. In practice, teachers can use only a subset of attributes to model their teaching subjects (or *LAs*), forming a *local measurement*, and optionally annotate attributes with subject-specific names if needed. Teachers can also put together local measurements to reveal a bigger picture on the all-round performance and development of a student, forming a *global measurement*.

SAM is modeled as a dot product of the attribute criteria matrix C, which comprises criteria for PAs (C_{PA}) and NPAs (C_{NPA}), and the score matrix, which comprises scores α_{ij}. As shown in Eq. (6.1), each criterion is modeled as a row vector A_i, which comprises a set of a_{ij} to model the different aspects of an attribute. For attributes from Bloom's taxonomy, each aspect corresponds to a level of complexity, while for attributes regarding learning styles and learning modes, each aspect corresponds to a characteristic of each learning style or learning mode. An aspect is modeled by a real number between 0 and 1 to represent its importance in a subject (or *LA*), where an aspect is set to be 0 if it is not being assessed. *To* model student learning state and teacher's expectation of a subject (or *LA*), as shown in

Eq. (7.2), we define a score matrix to comprise scores α_{ij}, where each score represents the level of achievement (or required efforts) of an aspect of a PA (or NPA). In an e-learning system, each subject (or *LA*) will associate with a SAM to define the teacher's expectation, while each student studying the subject (or *LA*) will be assigned with a SAM that is constructed by the same *C* to maintain the student's learning state.

$$C = \begin{bmatrix} C_{\mathrm{PA}} \\ C_{\mathrm{NPA}} \end{bmatrix} = [A_1, \ldots, A_i, \ldots, A_n]^{\mathrm{T}} = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n\mathrm{PA},1} & \cdots & a_{n\mathrm{PA},m} \\ a_{n\mathrm{PA}+1,1} & \cdots & a_{n\mathrm{PA}+1,m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \tag{7.1}$$

$$\mathrm{SAM} = \left\langle \begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} & \cdots & \alpha_{nm} \end{bmatrix}, \mathrm{C} \right\rangle = \begin{bmatrix} \alpha_{11}.\mathrm{a}_{11} & \cdots & \alpha_{1m} \cdot \mathrm{a}_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} \cdot \mathrm{a}_{n1} & \cdots & \alpha_{nm} \cdot \mathrm{a}_{nm} \end{bmatrix} = \begin{bmatrix} \mathrm{sa}_{11} & \cdots & \mathrm{sa}_{1m} \\ \vdots & \ddots & \vdots \\ \mathrm{sa}_{n1} & \cdots & \mathrm{sa}_{nm} \end{bmatrix} \tag{7.2}$$

Because a student will perform independently among different aspects of the attributes, each aspect could then be considered as a random variable, which follows the normal distribution $\mathrm{sa}_{ij} \sim N(\theta, \sigma^2)$ as shown in Eq. (7.3).

$$p(\mathrm{sa}_{ij}; \theta) = 1/\sqrt{2\pi}\sigma \cdot e^{-(\mathrm{sa}_{ij}-\theta)^2/2\sigma^2} \tag{7.3}$$

where p(·) is the probability distribution function of sa_{ij}; θ is the estimation value of sa_{ij}; σ^2 measures the width of the distribution. We use *maximum-likelihood estimation* [Kay93] to estimate θ, where the largest probability happens when sa_{ij} equals to θ, which is proved as a correct expectation of the observed data of sa_{ij}. So *SAM* could be dynamically updated by the mean value of all previous SAMs (Eq. 7.4).

$$\mathrm{SAM}(t) = 1/t \sum_{i=1}^{t} \mathrm{SAM}_i \tag{7.4}$$

where SAM_i only expresses the learning state for the *i*th *LA*. SAM(*t*) records the overall learning state of a student after learning *t LAs*. Because the change between SAM(*t*) and SAM(*t* − 1) may be perturbed by some uncertain factors and may not reflect the real learning performance, we consider averaging all previous learning performances to be the latest learning state of a student to reduce such an error.

Progress Potentiality Function (PPF)
To analyze the potentiality of a student for making progress in learning performance and for developing skills in non-performance-based attributes, we have developed a PPF to form a student achievement descriptor (Eq. 7.5).

$$P = f(L_{\text{PAs}}, L_{\text{NPAs}}) \tag{7.5}$$

where f(·) is the PPF, P is the student learning progress, L_{PAs} and L_{NPAs}, as shown in Eqs. (7.6) and (7.7), are the student learning performance in *PAs* and the degree of balance of a student's development in *NPAs*, respectively. A student has a higher potentiality to achieve more if the student can perform better in PAs and/or has a more balanced development in *NPAs*.

$$L_{\text{PAs}} = \sum_{i=1}^{n\text{PA}} \sum_{j=1}^{m_i} \text{sa}_{ij} \tag{7.6}$$

$$L_{\text{NPAs}}^{-1} = \left(1/n\text{NPA} \times \sum_{i=1+n\text{PA}}^{n} m_i\right) \sum_{i=1+n\text{PA}}^{n} \sum_{j=1}^{m_i} \left(\text{sa}_{ij} - 1/m_i\right)^2 \tag{7.7}$$

where m_i is the number of nonzero aspects for each attribute, *nPA* is the number of *PAs*, *nNPA* is the number of *NPAs*, and n is the number of attributes. $1/m_i$ is the perfect probability if *NPAs* can be developed evenly. Equation (7.6) reflects that for students who have higher value of learning outcome, their overall student learning performance could be higher as well. And Eq. (7.7) reflects that if the different aspects of non-performance-related attributes tend to be developed evenly, then the student can have a more balanced development in *NPAs*. We normalize the values of all L_{PAs} and ${L_{\text{NPAs}}}^{-1}$ to be within [0, 1] to allow them to be processed in a unified way. In the end, $f(\cdot)$ is given by $P = L_{\text{PAs}} + L_{\text{NPAs}}$.

Fuzzy Cognitive Map (FCM)
Existing work evaluates student learning progress mainly by their subject performance (PAs). However, student learning is a complicated process. Student learning performance can also be affected by NPAs, e.g., an active student tends to have better communication skills than a passive student. In addition, both PAs and NPAs may affect among each other. To model such complicated relationships and infer changes among the attributes, we apply Fuzzy Cognitive Map (FCM), which is formulated by Eqs. (7.8)–(7.10), to analyze changes of SAMs and infer the causal relationship among the attributes in a SAM.

$$F_j = f\left(\sum_{\substack{i=1 \\ i \neq j}}^{n} F_i f_{ij}\right) \tag{7.8}$$

where F_j and F_i are the state values of a pair of a starting attribute A_j and an ending attribute A_i, respectively. There are n attributes in total. The value of state F_j indicates the existent degree of a FCM node (i.e., an attribute). In our model, F_j reflects the overall strength of impact of an attribute on all the others, which can be formulated by the following:

$$F_j(t) = \sum_{\substack{i=1 \\ i \neq j}}^{n} F_i(t-1) \cdot f_{ij}(t) \tag{7.9}$$

where $F_j(t)$ is the state value of attribute A_j after finishing the tth LA. It is updated by the current causal weights f_{ij} from all the other attributes to attribute A_j together with the previous status values of all the other attributes. We assume all attributes having the same impact on each other at the beginning and set their initial state values to "1." Note that f_{ij} is represented by a real number within $[-1, 1]$ as it reflects the fuzzy meaning showing the impact degree from a starting attribute to an ending attribute, where $f_{ij} > 0$ (or $f_{ij} < 0$) implies increasing (decreasing) in the state value of a starting attribute, it will lead to an increase (decrease) in the state value of ending attribute. Otherwise, $f_{ij} = 0$ implies no causal relation existing between a starting and an ending attribute. The matrix of the causal weights forming the FCM is shown as follows:

$$\mathrm{FCM} = \begin{bmatrix} 0 & f_{12} & \dots f_{1n} \\ f_{21} & 0 & \dots f_{2n} \\ \vdots & \vdots & \ddots \vdots \\ f_{n1} & f_{n2} & \dots 0 \end{bmatrix} \tag{7.10}$$

After a student finished the current LA, the causal relationships among attributes are re-evaluated by taking mean of the Mahalanobis distances between the current and each of all previous SAMs, which essentially captures the changes of attributes of the SAMs. Because Mahalanobis distance can measure the similarity of an unknown multivariate vector to a known one (e.g., a group of mean values) and also measure the dissimilarity between two random vectors. The larger is d, the more dissimilar of the two vectors. d is 0 when the two vectors are exactly the same. The Mahalanobis distance is defined as Eq. (7.11):

$$d(\mathrm{SAM}_x, \mathrm{SAM}_y) = \sqrt{(\mathrm{SAM}_x - \mathrm{SAM}_y) S^{-1} (\mathrm{SAM}_x - \mathrm{SAM}_y)^{\mathrm{T}}} \tag{7.11}$$

where S is the Covariance matrix of SAM_x and SAM_y, which measures the dissimilarity of two matrixes, and is defined by Eq. (7.12)

$$S = \mathrm{cov}(\mathrm{SAM}_x, \mathrm{SAM}_y) = E\left[\left(\mathrm{SAM}_y - E[\mathrm{SAM}_y]\right)^{\mathrm{T}} (\mathrm{SAM}_x - E[\mathrm{SAM}_x])\right] \tag{7.12}$$

where $E(\mathrm{SAM}_x)$ is the expectation value of SAM_x. If we only measure the similarity of a specific attribute A_i, then the Mahalanobis distance turns to the following form:

$$d_i\left(\mathrm{SAM}_x, \mathrm{SAM}_y\right) = \sqrt{\left(\mathrm{SA}_{ix} - \mathrm{SA}_{iy}\right) S^{-1} \left(\mathrm{SA}_{ix} - \mathrm{SA}_{iy}\right)^{\mathrm{T}}} \tag{7.13}$$

where S turns to

$$S = \operatorname{cov}\left(\mathrm{SA}_{ix}, \mathrm{SA}_{iy}\right) = E\left[\left(\mathrm{SA}_{iy} - E\left[\mathrm{SA}_{iy}\right]\right)^{\mathrm{T}} \left(\mathrm{SA}_{ix} - E[\mathrm{SA}_{ix}]\right)\right] \tag{7.14}$$

Hence, the causal weights f_{ij} of FCM can then be dynamically updated. Such calculations are shown by Eqs. (7.15)–(7.17).

$$\begin{aligned} f_{ij}(t) &= \begin{cases} \frac{1}{\frac{(t-1)t}{2}} \left(\frac{(t-2)(t-1)}{2} f_{ij}(t-1) + \sum_{x=1}^{t-1} y_{ij}(k,t) \right) & i \neq j \\ 0 & i = j \end{cases} \\ &= \begin{cases} \frac{t-2}{t} f_{ij}(t-1) + \frac{2}{t(t-1)} \sum_{x=1}^{t-1} y_{ij}(k,t) & i \neq j \\ 0 & i = j \end{cases} \end{aligned} \tag{7.15}$$

$$y_{ij}(k,t) = \frac{\mathrm{Sign}_i \cdot d_i(\mathrm{SAM}_k, \mathrm{SAM}_t)}{\mathrm{Sign}_j \cdot d_j(\mathrm{SAM}_k, \mathrm{SAM}_t)} \tag{7.16}$$

$$\mathrm{Sign}_i = \mathrm{sign}\left(\sum_{\text{level}=1}^{\text{num of levels}} \left(\mathrm{SA}_{i,k} - \mathrm{SA}_{i,t}\right) \right) = \begin{cases} 1 & \text{progress} \\ -1 & \text{regress} \end{cases} \tag{7.17}$$

where $f_{ij}(t)$ expresses a causal weight after a student finished the tth *LA*, and $k \in [1,\ t-1]$ is the index of previous $t-1$ activities. Since the changes of attributes are measured between the current SAM and each of the previous SAMs, after a student finished studying a new *LA* (i.e., a new SAM is generated), there will be $(t-1)t/2$ times comparisons in total. $y_{ij}(k,t)$ models how much A_j will change relative to the change of A_i between SAMs obtained at the tth and the kth *LAs*, where $d_i(\mathrm{SAM}_k, \mathrm{SAM}_t)$ is the Mahalanobis distance of these SAMs. Sign_i equals to 1 if the student makes progress, otherwise it equals to -1.

7.2.2 Student Progress Indicators

Learning Attribute and Student Groups

To analyze the student learning progress and development, we need different kinds of groupings, namely *learning attribute groups* (*LAGs*) and *student groups* (*SGs*). LAGs are formed to support local measurement. They comprise groups to maintain subsets of learning attributes. These groups are as follows:

- **Subject Group**: to assess subject (or *LA*)-specific knowledge or skills. In our experiments, we maintain groups for Arts, Science, and all subjects.

- **Learning Stage Group**: to assess students at appropriate cognitive levels during different stages. Learning stages contain three stages to imitate students' early, interim, and mature stages, respectively. The early stage assesses students' basic knowledge in cognitive levels. The interim stage assesses student learning progress potentiality in non-performance-related attributes as well as attributes in Affective and Psychomotor domains to monitor whether they have balance development. And the mature stage assesses students' advanced knowledge in cognitive levels.

SGs are formed to support a more holistic analysis. They can be constructed manually or automatically, which include the following:

- **Study Group**: to divide students based on subject of study, e.g., Arts and Sciences. We also consider individual or all students as general groups. All these groups' types are manually predefined.
- **Performance Group**: to divide students based on their learning performance associated with skills. Teachers are expected to apply their experience to define groups of best, good, satisfactory, below average, and disqualified students, which form *performance metrics* describing teacher's expectation on students with different learning performances.

Such metrics may also be automatically generated by applying performance information from the former cohorts. Because we also define students' attribute values in a fuzzy meaning which indicates the degree of requirements for each aspect, we can apply these fuzzy values to measure the degrees of belonging to clusters. And in Fuzzy C-mean clustering method, each point has a degree of belonging to clusters, rather than belonging completely to just one cluster. Points on the edge of a cluster may have a less degree than points in the center of cluster. When analyzing students' actual performance, we apply the Fuzzy C-mean clustering method [Bezd81] to divide students into groups based on their SAMs, where the student learning performance metrics defined by teachers forming the representatives of the clusters.

Formulation of Student Progress Indicators

Student learning progress indicators are functions developed to produce information for pedagogically depicting student learning progress and development. There are three indicators:

- **Knowledge Construction Indicator (KCI)**: Inputs of KCI are PAs, NPAs based on selected LAGs. It produces the learning status of a student with respect to certain learning stage by evaluating the updated SAM and FCM, followed by classifying the student into a proper performance group. KCI offers comprehensive information describing how a student performs.
- **Teacher's Expectation Indicator (TEI)**: Inputs of TEI are a set of KCI based on selected LAGs and SGs, i.e., collective information indicates the learning progress and development from a group of students. Based on the performance metrics, TEI produces a picture on how a selected group of students make

progress against the teacher's expectation, for instance, showing whether there are too many students perform significantly better than what a teacher expected. In such a case, the teacher may conclude the course is too easy.

- **Student Growth Indicator (SGI)**: Inputs of SGI are a number of sets of PAs and NPAs of a student or a group of students from certain series of learning stages, i.e., the learning progress and development made by certain student(s) over a period of time. SGI evaluates PPF based on the inputs to indicate whether certain student(s) make progress or regress over time.

According to the above description, we can provide with Eq. (7.18) to present the whole idea of student(s) learning progress.

$$(\mathrm{SP}, t) = f(s_1, s_2, \{\mathrm{LS}, g\}, a) \tag{7.18}$$

where $f(*)$ presents the function of *type of student*(*s*) (s_1), *selected subjects* (s_2), *learning stage* (*LS*) or the general *growth* (g)over time, and *attributes*' *performance* (a). The type of student(s) could be a type of student group, an individual student, or all students. And *attributes*' *performance* could be learning performance on *PAs* or balance degree of *NPAs*. We can get the student(s)' *learning progress* (*SP*) and *teacher*'*s expectation* (t) with $f(*)$ for the *type of students* (s_1) in the corresponding *subjects* (s_2) and *attributes*, and corresponding *learning stage* (*LS*) or the general *growth* over time (g).

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Chapter 8
Implementation and Results

8.1 Implementation for Method for Constructing a Fine-Grained Outcome-Based Learning Path Model

To answer the first research question of how to learn, which requires finding out the teaching approaches and the sequence of learning, we have proposed a fine-grained outcome-based learning path (LP) model. In order to verify this method, we have implemented a prototype of this model. Next, we conduct a user study, in which we have invited teachers to try out our prototype and evaluate it as well as give us feedbacks in terms of their user experiences. This user study is mainly carried out through 3 parts including an introduction on the system, user interaction with the prototype, and evaluation questionnaires. We then collected teachers' feedback on the questionnaires, and use one-way ANOVA to analyze the collected data. During the one-way ANOVA analysis, we group teachers according to their teaching experiences and knowledge backgrounds, respectively, so that we can determine if teachers with different teaching experiences or different knowledge backgrounds would have different evaluation results on our system.

8.1.1 Instrument

In order to verify our work, this monograph has implemented the prototype of the fine-grained outcome-based LP model, so that we can ask teachers to evaluate our method through a user study.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_8

8.1.1.1 Implementation

This prototype provides teachers the basic functionality of designing LP, where teachers can create or delete learning activities, learning tasks, as well as adjust their settings and teacher can create and manipulate LP components graphically. And also, this prototype provides the corresponding LP of student learning performance. The prototype implementation help teachers to better understand how they can manage and design the LP for different types of students. I have applied Jgraph, Ext JS, PHP, MySQL, and Apache, etc. to implement the prototype. The implementation details are explained in Sect. 4.5.

8.1.1.2 User Study

We also conducted a user study for teachers to evaluate our work, which includes three parts, an introduction on the system, user interaction with the prototype, and evaluation questionnaires. Teachers are firstly invited to experience this prototype. They can ask questions about it to help them to understand how to manage it. Afterwards, they are given a questionnaire to collect their evaluations of this LP model. The whole questionnaire (Appendix A) contains 19 questions, where the first 6 questions collect information about teachers' personal teaching information, and the rest questions can be divided into three major questions: (1) Can the new model provide a more systematic and intuitive way for teachers to construct LPs? (2) Does it produce LPs that address the diverse needs of different courses? (3) Do teachers think that it is easier to set out criteria to assess student learning outcomes through the new model? Teachers are expected to scale each of these questions using 5-point likert scale to indicate their satisfaction on our work. With these statistic data, we can analyze if teachers satisfy with our work.

8.1.2 Participation

We evaluate the fine-grained outcome-based LP model by testing if teachers with different teaching experience or knowledge backgrounds would have different evaluation results on our model. We invited 15 teachers who all have different teaching experience and from different subject disciplines. These teachers are from Durham University and some local high schools. And they all have experience of using E-Learning systems, so that they can provide more professional feedbacks.

8.1.3 Data Analysis

As we use questionnaires as the research instrument to collect teachers' evaluation results on our work, where we have scaled these questions with 5-point likert scale, so that we can quantify teachers' evaluation results and provide numerical analysis using statistic method like one-way ANOVA.

Likert Scale: In the questionnaire, each question for evaluating our model has 5 options (Totally Agree = 5, Agree = 4, Neutral = 3, Not Quite Agree = 2 and Disagree = 1), teachers can select the options that best fits their decisions. The quantified answers help us to measure teachers' overall satisfaction on our model.

One-way ANOVA: In the study, we analyze if teachers' teaching experience and knowledge backgrounds will affect their evaluation results. We divide teachers into several groups according to their teaching experience and knowledge backgrounds to compare if their evaluation results are similar or not. Because one-way ANOVA is used to compare the similarity between data in two or more groups, but the size of these groups does not need to have exactly the same number, we can apply one-way ANOVA to compare the results. After we obtain teachers' evaluation results by the likert scale measurement, we can use the 'one-way ANOVA' functionality of 'Data analysis' provided by Microsoft Excel software to automatically calculate if the evaluation results among different groups are similar or not.

8.1.4 Implementation

To evaluate our work, we have implemented a prototype system based on our fine-grained outcome-based LP model. We use PHP and Javascript as the server-side scripting language, Apache as the Web server, MySQL as the database, and Windows as the operation system to implement this prototype, and use the graph visualization library JGraph to generate diagrams. The prototype comes with a drag-and-drop graphical user interface assisting teachers to create and manipulate LP components graphically. The prototype is not currently a functioning learning management system, where content management was not implemented. Figure 8.1 shows a screen shot of our prototype where a teacher is working on a *LA* level LP that comprises learning activities for all students in a computer science program. As shown at the upper part of Fig. 8.1, there is a menu providing some predefined learning activities for the teacher to construct LPs. Under the menu, there is an area for LP construction. Each of the test users was invited to attend a personal introductory session, which lasted for about an hour. Each session started with a briefing on the proposed LP construction model. They can ask questions during the briefing if they have anything confused. The test user then had a chance to use the prototype to construct LPs and was required to answer a questionnaire to comment on the prototype. The questionnaire contains questions to collect teachers' background information as well as to collect teachers' evaluation results on our prototype from both choice questions and written form. More details about the whole questionnaire are listed in Appendix A.

Figure 8.1 shows a sample LP constructed by a teacher. As an example, a "Lecture" type of learning activity—"Computer Networks (*LT*)" is constructed in Semester 2, which can be further customized by modifying its learning tasks and

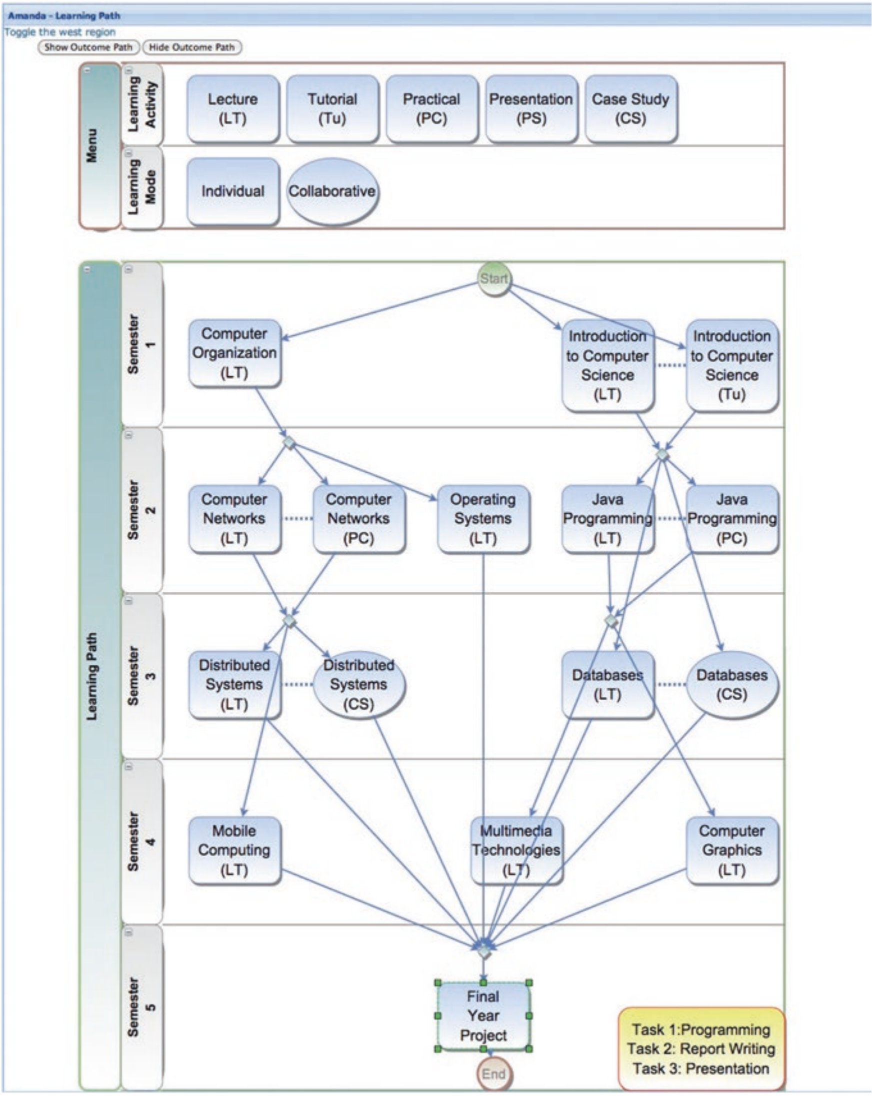

Fig. 8.1 A screen shot of our prototype

their associated weights. For instance, *LA* "Final Year Project" is selected to reveal its learning tasks, which are shown in the yellow box located at its right hand side. Teacher can overview the learning tasks contained in the learning activity before he/she decides to change the task arrangement of the learning activity by opening another window. In addition to "Computer Networks (*LT*)", a "Practical" type of learning activity—"Computer Networks (PC)" is constructed. These two learning activities come together forming a KE, which is indicated by a dashed-line connection. This KE formulation allows students to follow multiple approaches when learning a subject and achieve more learning outcomes.

A student may conduct a learning activity if he/she has passed all pre-requisite(s). Note that arrows indicate pre-requisites, while rhombuses indicate multiple learning activities sharing the same pre-requisites or learning activities having multiple pre-requisites, e.g., "Distributed Systems" has both "Computer Networks (*LT*)" and "Computer Networks (PC)" as pre-requisites. Optionally, a LP can be turned into an adaptive one if suitable types of learning activities can be set up for each student. Despite this feature surpasses existing KE-based methods where they do not support the modeling of pedagogy and certain forms of learning outcomes. However, further techniques should be developed to avoid teachers manually producing all settings.

Teachers then proceed with more fine-grained settings. Our prototype provides interfaces for teachers to define and review learning outcome settings at both learning stage and learning activity levels. Figure 8.2a shows a learning stage—"Semester 1" is selected. Its learning outcome settings shown in Fig. 8.2b, indicating Semester 1 assesses student learning outcomes based on *knowledge*, *comprehension* and *application* levels under the cognitive domain of Bloom's Taxonomy. The chart also shows the total percentage of each learning outcome collected from all learning activities within the learning stage to indicate its importance. Such weights cannot be adjusted.

We also ask teachers to work on individual learning activity. Figure 8.1 shows that learning activity "Computer Organization (*LT*)" in Semester 1 is selected for editing. The lower part of Fig. 8.2b shows its settings with editable learning tasks, i.e., *Reading*, *Discussion* and *Question*. The prototype can automatically normalize the weights of all learning tasks based on the weight adjustment mechanism described in the sub-section of "Learning Activity" under Sect. 5.3. This feature is handy, allowing a teacher to focus on the relative importance of learning tasks rather than the actual values of the weights. In addition, a teacher can change the learning outcome setting of a learning task by dragging-and-dropping learning outcomes from the learning outcome requirement menu, as shown in the upper part of Fig. 8.2b.

For demonstration purpose, our prototype also supports basic learning progress evaluation. We classify a student's learning outcome of a learning activity with a few grade levels, ranging from "Fail" to "Excellent". As shown at the top of Fig. 8.3, they are represented by different colors. Figure 8.3 shows that a student has just completed Semester 1, and has received a "Good" learning grade in "Computer Organization (*LT*)" but failed in both the "LT" and "Tu" learning activities of "Introduction to Computer Science"(in pink color). Based on the setting of our prototype, this student needs to retake these failed learning activities before starting Semester 2 (Fig. 8.4).

Our prototype also supports the construction of the *LT* level LPs to indicate how a student is being trained in terms of a specific type of student learning outcome. This function can be activated by pressing the "Show Outcome Path" button at the top-left side of the user interface shown Fig. 8.3a. Figure 8.5 shows the *LT*

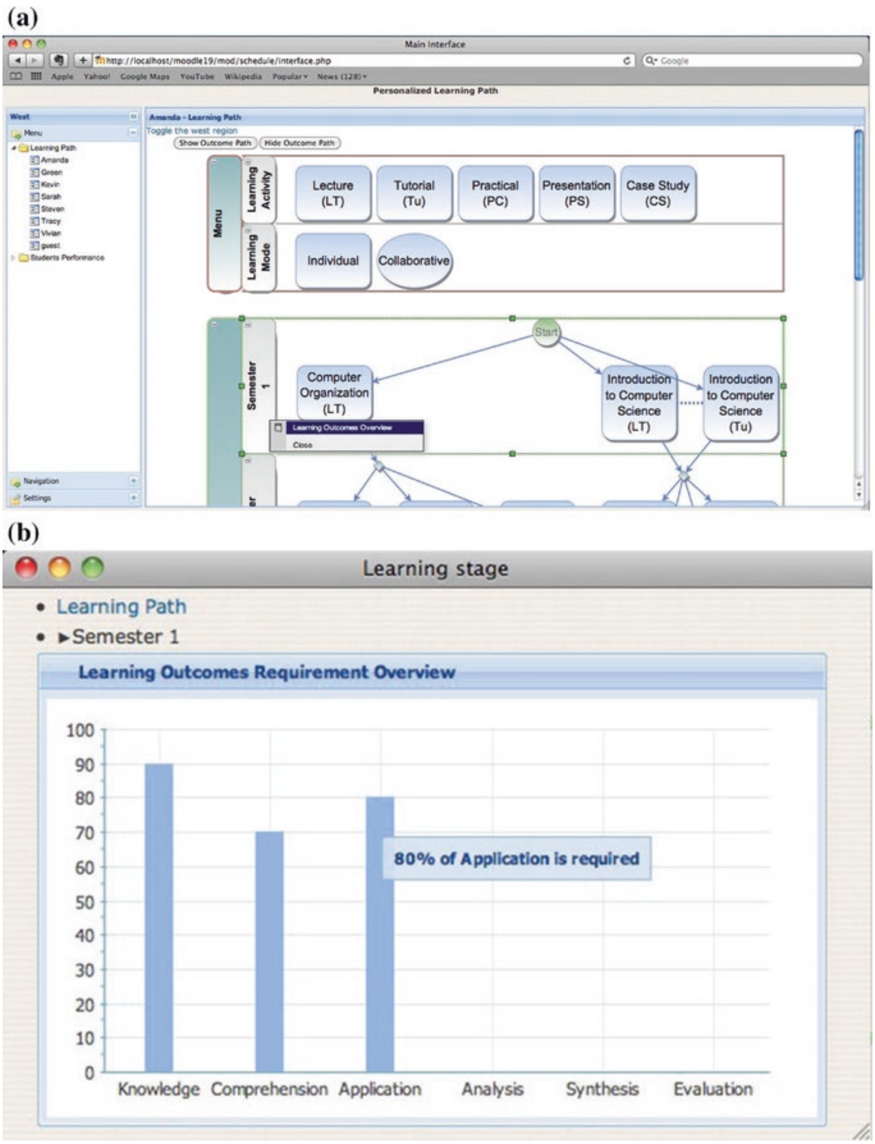

Fig. 8.2 Viewing the learning outcome setting at the learning stage level

level LP for communication skill while Fig. 8.6 shows the path for writing skill. To illustrate the assessment of learning outcome, we use a percentage value to show the difficulty level of certain learning outcome required at a *LA*. If the student can pass the assessment associated with the corresponding *LT*, it means that the student has made the prescribed level of achievement in that particular learning

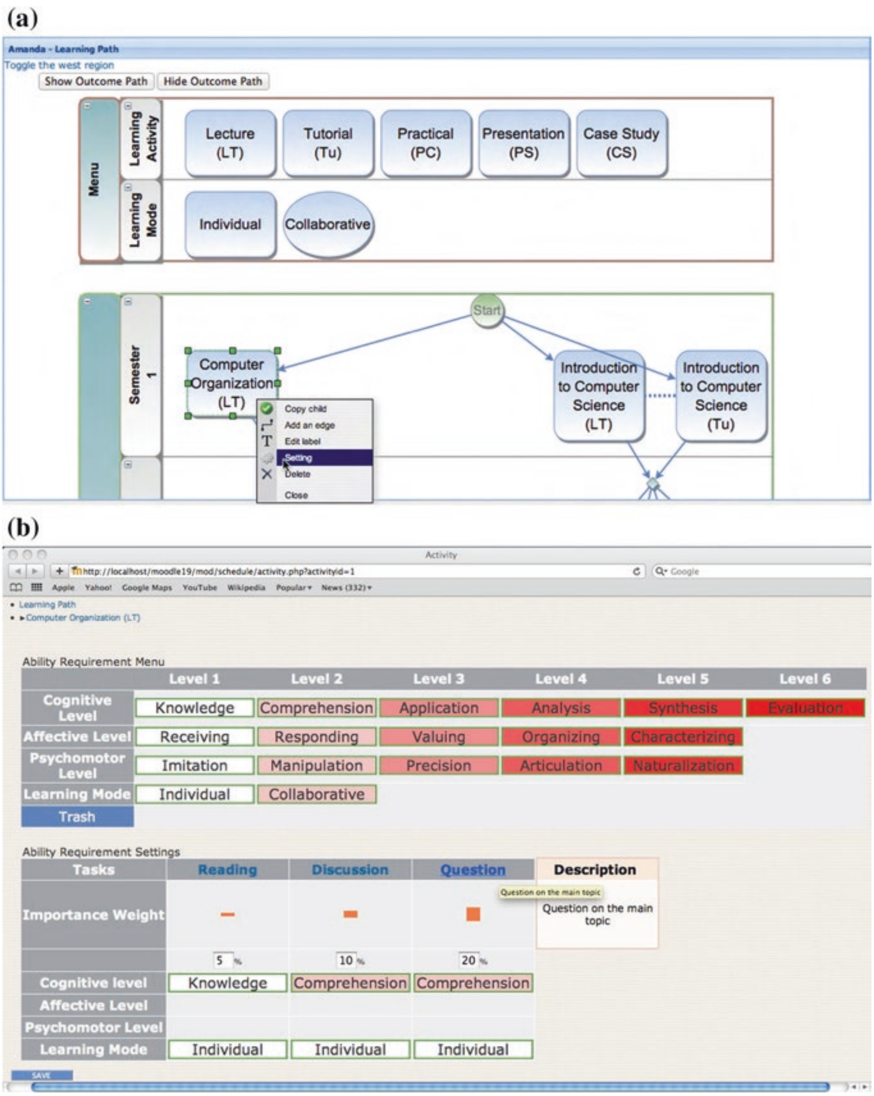

Fig. 8.3 Manipulating the learning outcome setting at the learning activity level

outcome. Using Fig. 8.5 as an example, at the beginning, two *LAs* are involved in Semester 1 to train up a student's communication skill. The difficulty levels of both are set to 20 %. As a student proceeds with the course of study, the student may gain a higher level of achievement in communication skills. This is shown by the increase in the difficulty level associated with the communication skill along the LP. Finally, after the student has gone through the entire course of study, the student is expected to have gained very mature communication skill with the

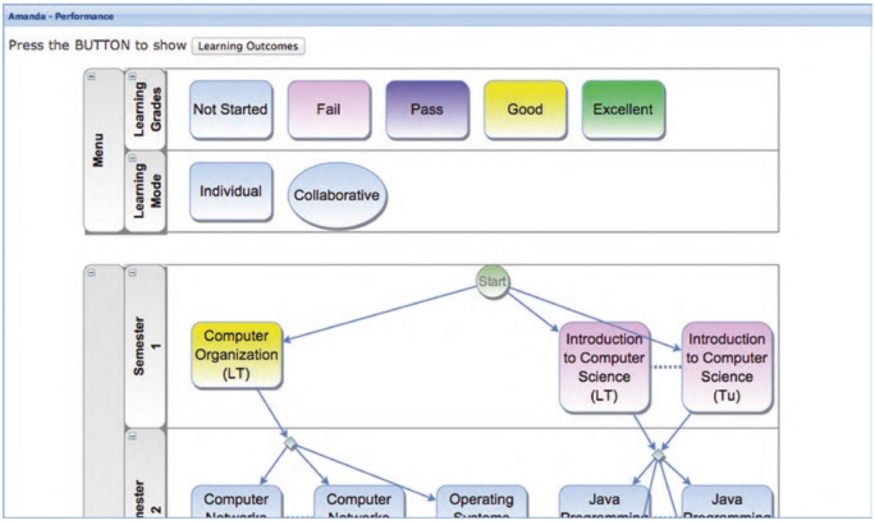

Fig. 8.4 A screen shot showing the progress of a student

100 % of difficulty level, if the student can pass the assessment of the corresponding *LT* set in the "Final Year Project" learning activity in Semester 5. In general, the *LT* level LPs help students to learn more effectively by letting them understand how well they have achieved in certain learning outcome. In case if a student fails in certain learning outcome, the student can be supported by re-doing only the relevant learning tasks in order to fix such a learning problem. This fine-grained arrangement can enhance the learning effectiveness as it avoids the students re-doing the entire learning activities or KEs.

8.1.5 Experiment Results

Following the case study as depicted in Sect. 8.1.4, we have delivered a questionnaire to collect teachers' feedback on the proposed LP model. The evaluation model and the results are shown as follows:

Research question: We tested whether teachers of different (1) knowledge background or (2) teaching experience will find our model providing a good way for constructing LPs and assessing student learning outcome. Our prototype is designed to let teachers visualize and try out our model. We do not evaluate the user interface design of the prototype, as it is out of the scope of this research. We invited teachers from Durham University and some local high schools to try out our prototype and give us feedback of their satisfaction on our LP model by using 13 questions to access the following research questions:

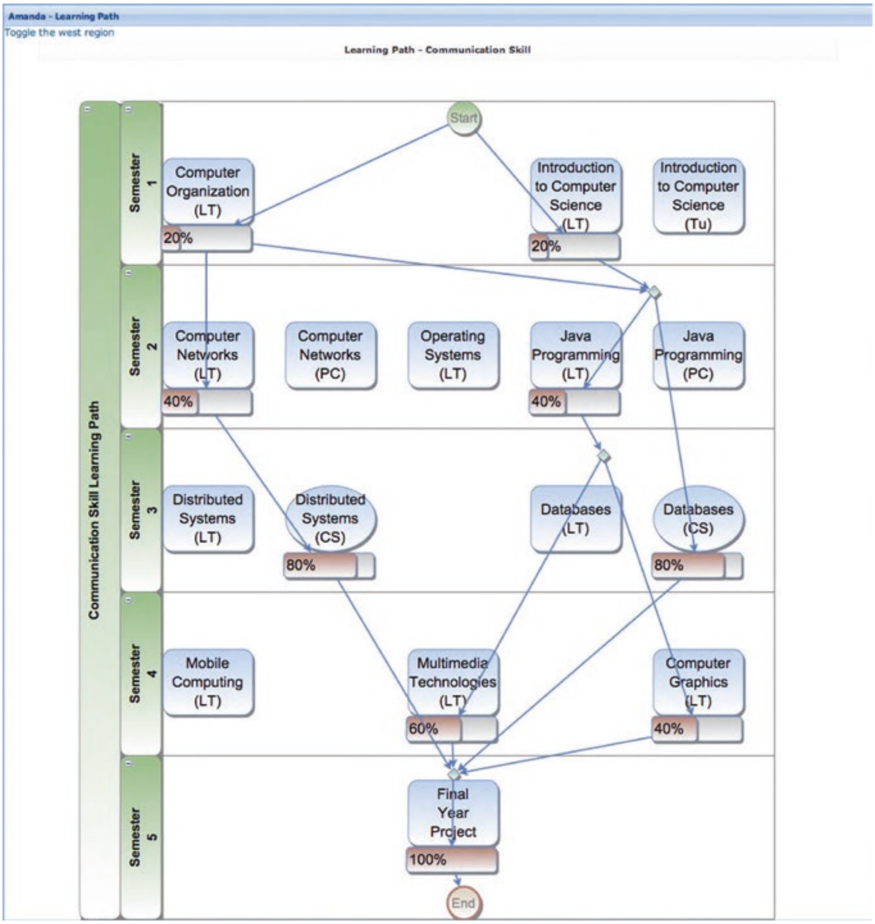

Fig. 8.5 Learning path for communication skill

- **RQ1**: Can the new model provide a more systematic and intuitive way for teachers to construct LPs?
- **RQ2**: Does it produce LPs that address the diverse needs of different courses?
- **RQ3**: Do teachers think that it is easier to set out criteria to assess student learning outcomes through the new model?

The questions provide proper coverage for evaluating both the LA and LT levels of LP construction. Teachers were required to provide feedback on the 13 questions based on a 5-point likert scale (Totally Agree = 5, Agree = 4, Neutral = 3, Not Quite Agree = 2 and Disagree = 1). As we use continuous and ordered rating scales, where they are assumed to have equal intervals and implicitly approximate interval data, they are quantitative and allow us to use ANOVA [Kirk95] for analysis. We also have another 5 questions collecting personal information of a teacher,

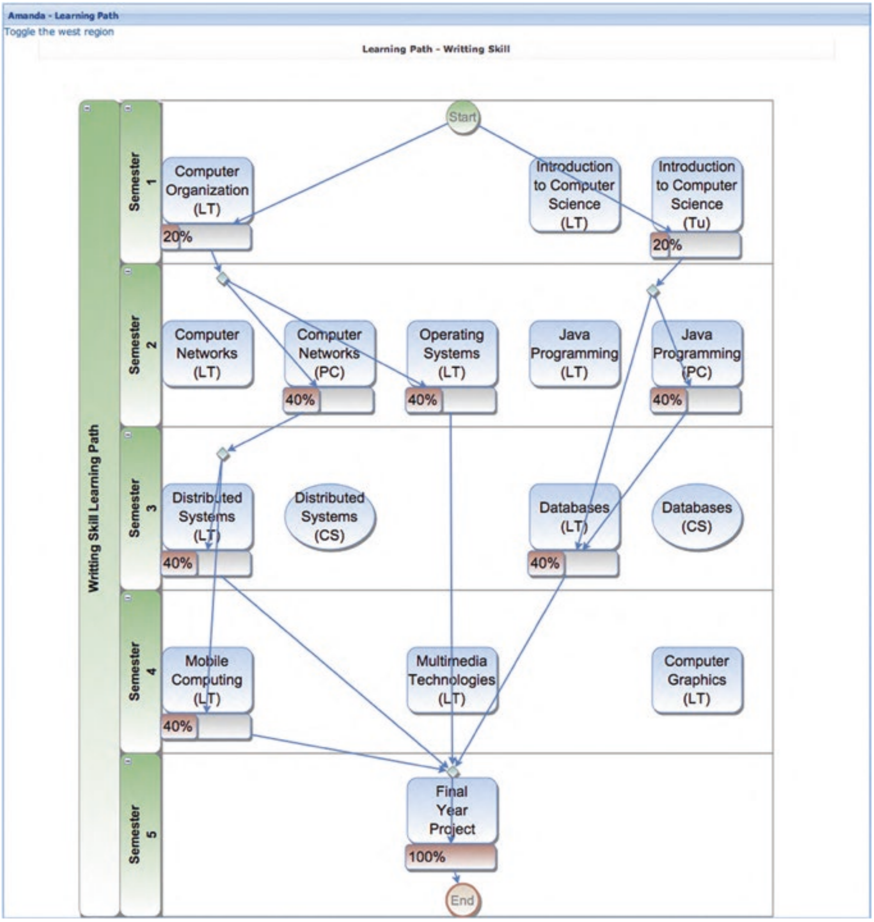

Fig. 8.6 Learning path for writing skill

including teaching experience, teaching discipline, e-learning tools experience, and teaching approaches and styles.

Sample building: 15 teachers were involved in the experiment. The independent variables are (1) knowledge background (KB) and (2) teaching experience (TE), where each of them is classified into groups of samples as follows for analysis.

- **Groups under KB**: Science (7 teachers), Engineering (6 teachers) and Arts (7 teachers).
- **Groups under TE**: 0–1 year (6 teachers), 1–4 years (4 teachers), 5–9 years (5 teachers), and 10 years or above (5 teachers).

Note that we did not use a control group as all the teachers in our experiment have experience in using e-learning tools, such as Wimba Create, Blackboard, Learning

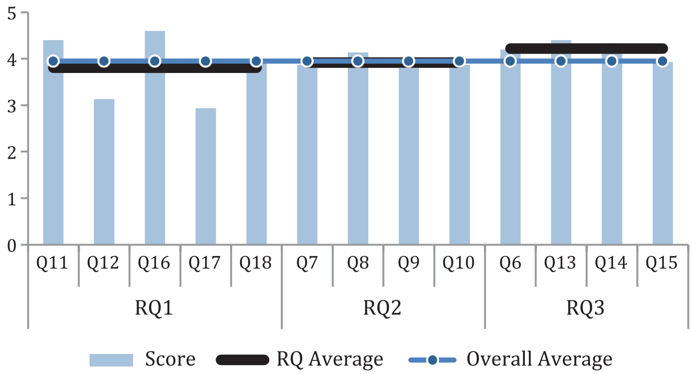

Fig. 8.7 Summary of scores from the questionnaire

Object (LO) Creator and Web tools. Some of them have even involved in designing or modifying teaching activities. This indicates most of our test users have a good understanding in difficulties and important factors of LP design. Therefore, besides the ANOVA analysis, we also collect opinions from the teachers regarding their experience with our model.

Statistical model: We employ one-way ANOVA to analyze each of the independent variables because both variables comprise more than two groups. Methods that can analyze only two groups, such as Wilcoxon test, are not applicable.

Statistical results and conclusions: As shown in Fig. 8.7, the teachers have rated an overall average score of 3.95 out of 5 with the 13 questions, meaning that they have a very good satisfaction of using our model across different aspects of LP construction. More specifically, the average scores of individual group of questions are 3.81 (RQ1), 3.92 (RQ2) and 4.22 (RQ3). While teachers have a very good satisfaction on our model regarding intuitiveness and meeting diverse needs, they rate much higher on our model in terms of assessing student learning outcomes. Note that the scores of Q12 and Q17 are rated lower than the other questions. They asked feedback on whether the prototype can clearly show the relationship among LAs and the design of a LP, respectively. The lower scores are related to the user interface design of the prototype. Although this issue is out of the scope of this research, we believe this is an important issue to work on for our future work, particularly it relates to how we can avoid putting burden on teachers to work out mathematics for setting up LPs and learning activities.

In general, the teachers agree that incorporating learning outcomes from the Bloom's Taxonomy is useful, and they feel that the introduction of *learning task* is good as it allows a teacher to focus on designing simple tasks to train up students with a specific learning outcome. They are in favor of the idea of *learning activity*, which comprises learning tasks, as it is more intuitive for teachers to create and organize learning activities. According to the results of one-way ANOVA, no

Table 8.1 Results of one-way ANOVA analysis

ANOVA single factor: knowledge background						
Source of variation	SS	d*f*	MS	*F*	*P*-value	*F* critical
Between groups	0.670139	2	0.335069	0.899926	0.416344	3.284918
Within groups	12.28688	33	0.37233			
Total	12.95702	35				
ANOVA single factor: teaching experience						
Source of variation	SS	d*f*	MS	F	*P*-value	F critical
Between groups	1.353611	3	0.451204	1.162679	0.334742	2.816466
Within groups	17.07519	44	0.388072			
Total	18.4288	47				

statistically significant differences in teacher evaluations were found due to knowledge background or teaching experience.

We set p-value to 0.05, meaning that our test is based on the assumption that the probability of getting statistically significant results simply by chance is less than 5 %. As shown in Table 8.1, when performing AVONA test on teacher's knowledge background, F-value is 0.8999 and p-value is 0.4163 when df_1 between the 3 groups is 2 and df_2 within the groups is 33. As F-value is close to 1 and p-value is much greater than 0.05, there is not a statistically significant difference between the means of all groups, and the difference in teaching experience is not statistically significant to the teachers' evaluation. Similarly, the same conclusion can be drawn when we perform AVONA test on teacher's teaching experience, as F-value is 1.1627 and p-value is 0.3347 when df_1 between the 4 groups is 3 and df_2 within the groups is 44.

Analytical Comparison: To depict the differences between our model and existing methods [Chen08, Cono05, Dalz03, Kara05, Limo09]. We examine the nature of the constructed LP and the nature, the number and the sequence of the LOs used to build a LP from different methods. Table 8.2 summarizes the comparison. The most significant difference of our model is that it offers multiple LPs to support various forms of student learning outcomes assessment on top of the traditional functionality of a LP, which models the steps of a course of study. In contrast, existing methods only support the traditional functionality and offer a single LP. As a result, student learning outcome assessment is only a consequence of such a modeling, and that various types of student learning outcomes assessment are hard to be supported. Regarding LOs, existing work use a KE or a LA to form a LO, and that they determine the number and the sequence of LOs. In contrast, we model a LO with two levels: LA or LT based, which leads to two different types of LO sequences.

Table 8.2 Comparison between our model and existing methods

Comparison criteria	Methods		
	Our model	Chen et al. [Chen08], Karampiperis et al. [Kara05], LS-Plan [Limo09]	LAMS [Cono05, Dalz03]
Constructed LP(s)	Multiple LPs with 2 levels: LA and LT based (support fine-grained pedagogy)	Single LP: KE based (pedagogy is not supported)	Single LP: LA based (support coarse-grained pedagogy)
Nature of LOs	Formed by LAs or by LTs (relevant LAs can form a KE)	Formed by KE	Formed by LA (no explicit LA and KE mapping)
Number of LOs	Determined by number of LAs or by number of LTs	Determined by number of KEs	Determined by number of LAs
Sequence of LOs	Ordered by LAs or by LTs	Ordered by KEs	Ordered by LAs

8.1.6 Summary

In this section, we have presented a novel LP model based on learning activities, which supports the assessment of various types of knowledge and skills to describe the student learning progress. We have mathematically defined the model, its components, and the relations and constraints among the components, allowing course designers or teachers to explicitly formulate and reuse the learning and teaching approaches. Our work may also open up new research and development on more advanced adaptive E-Learning systems that can incorporate precise teaching approaches to match with different student learning styles. We have implemented a prototype and conducted a user study to verify if the proposed model can match with the teachers' needs well. Results show that our model is favorable and most of the teachers participated in the user study indicated that they would like to use it in their course design.

Our work may open up new research and development on more advanced adaptive E-Learning systems that incorporate precise teaching approaches to match with different student learning styles. We believe that while an automatic LP generation method is desired, teachers may still want to have the flexibility for manually customizing a LP. In our opinion, a sensible solution should aim at avoiding teachers to spend time explicitly setting up a lot of mathematical parameters for students with different learning styles. In this sense, we determine user interface design and setting up templates for LPs and their components could be two possible directions for future work. For user interface design, similar to our prototype, we should work out visual aids and manipulators for teachers to adjust and visualize the importance of each LP component. As a complement, techniques should be developed for producing templates for LPs and their components. We may also extend existing work on adaptive LP generation, such as [Li10, Ullr09], to work with the template based idea to produce adaptive fine-grained LPs.

8.2 Implementation for Learning Path Construction Based on Association Link Network

To answer the second research question of what to learn, which requires finding out the learning outcomes that students are going to achieve and the learning resources that help students to achieve the learning outcomes, we have proposed a LP construction method based on Association Link Network. This method can construct personalized LP from well-structured learning resources. In order to verify this method, we have implemented a prototype system of this model as well. Next, we have conducted two experiments to show the advantages of the system recommended ones. One is to compare the quality of manually selected LPs with system recommended LP, and the other is to compare student learning performance after using manually selected LP and system recommended LP. In the second experiment, as we have two groups of data, so we applied two sample *T*-tests to analyze the differences between the learning performance of the two groups of students.

8.2.1 Instrument

In order to verify this work, we implemented a prototype of LP construction system, with which we can ask both teachers and students to evaluate the system through a comparison study.

8.2.1.1 Implementation

To evaluate the performance of the LP that is constructed based on Association Link Network, the implemented prototype of the LP construction system graphically shows how learning resources are related to each other as well as support the editing of teacher knowledge model. Teachers can adjust the structure of teacher knowledge model. And students can learn tailored learning resources through associations of these learning resources in the keyword, concept, and learning resource ALNs, respectively. I have applied Tomcat, Web Services, and JSP, etc. to implement the prototype. More details about these implementation tools are explained in Sect. 4.5.

8.2.1.2 Comparison Study

We then conduct a comparison study to evaluate the method in two aspects. One is to compare the importance of system recommended LP with the manually selected LPs, the other is to compare student performance between students who use this system and the students who do not use the system.

In the first experiment, importance of LP is evaluated by summing up the importance of the nodes that constitute a LP. Teachers are asked to manually construct LPs according to the topic ALN. Such a construction should fulfill two requirements: (1) the selected topics should connect with each other; (2) the selected topics should be important to students. Such requirements also govern how the recommended LP generated by our system. To determine whether the comprehensiveness of the ALN structures will affect the quality of LP generation, we conduct experiments using three different abstraction levels of TKM by changing the number of association links constituted the topic ALN. Particularly, we use topic ALNs that have 196 links, 271 links and 360 links, corresponding to 20, 50, and 80 % of the total association links, to form the low, middle and high resolutions of TKM, respectively.

In the second experiment, we randomly divide students into two even groups. The 1st group of students perform learning based on the teacher constructed LPs, while the 2nd group of students learn by the system recommended LP. All students are given 50 min for studying the learning resources in the LPs, and take the same examination with 25 questions to assess their understanding. Given their answers of these questions, we can compare their performance, and also compare if their performance is stable.

8.2.2 Participation

To complete the evaluation of the LP construction based on Association Link Network, we have invited both teachers and students to help us to complete the comparison study. The 10 teachers are invited from Computer Sciences Department to manually select LPs which are used to make comparison with system recommended LP. We also invited 10 postgraduate students from Computer Science Department, but they have different learning abilities, i.e. they perform differently when studying the same LR. We randomly divide them into two even groups. The 1st group of students learn by the manually selected LP, while the 2nd group of students learn by the system recommended LP.

8.2.3 Data Analysis

We conducted two comparison studies to evaluate the work of LP construct. Firstly, we applied the ratio of system recommended LP and manually selected LPs, in order to verify that our work can provide a LP with higher importance degree in terms of covered knowledge concepts. Secondly, we used independent two-sample *T*-tests to compare the learning performance of two groups students who used our method and who did not use our method.

Ratio: Ratio is a type of measurement of scale. In the first comparison study, the ratio is made of the importance degree between system recommended LP and manually selected LPs. It measures the differences between the two paths and shows how their differences change over when the size of teacher knowledge model is different.

Independent Two-sample *T*-tests: When the number of groups for comparison is two and the size of each group is the same, then ANOVA turns to be the independent two-sample *T*-tests. In order to verify that students using system recommended LP have better learning performance, we use the independent two-sample *T*-tests to compare the differences of student learning performance variances between the group of students who use our Association Link Network based LP construction model and the group of students who do not use our model.

8.2.4 Evaluation Results and Analysis

In order to show the advantage of the system recommended LP, we have conducted a quantitative analysis showing the importance of LP for both system recommended one and manually selected ones to make comparison of the two LPs. We also conduct a qualitative analysis explaining the comparison results. And also, in order to compare student learning performance based on the teacher generated LPs and the system recommended one, we show the performance for the two groups of students by graphs, quantitatively analysis the improvement of their performance and their stability of their performance, and qualitatively explain the results.

8.2.4.1 Compare the Importance of Manually Selected and System Recommended Learning Paths

In this experiment, importance of LP is evaluated by summing up the importance of the nodes that constitute a LP. Ten teachers from the School of Computer Science, Shanghai University, are asked to manually construct LPs that comprise 5 nodes (i.e. topics) from the topic ALN of teacher knowledge model. They are asked to construct a LP that should fulfill two requirements: (1) the selected topics should connect with each other, and (2) should be important to students. Such requirements also govern how the recommended LP generated by our system. We can compare the LPs selected by teachers and the LP recommended by our system. Because we want to test if the complexity of TKM will cause any effect on teachers' decision as well as on our system recommendation results, we choose 3 topic ALNs which have different number of links. Particularly, we use topic ALNs having 196 links, 271 links and 360 links, which correspond to 20, 50, and 80 % of the total association links, forming the low, middle and high resolutions of TKM, respectively. So teachers actually need to select 3 LPs from each of these TKMs. Correspondingly, system recommends 3 LPs according to the 3 resolutions of TKM. Results show that the importance of system recommended LP is higher than that of the manually selected LPs. To determine whether the comprehensiveness of the ALN structures will affect the quality of LP generation, we conduct experiments using three different resolutions of the TKM by changing the number of association links constituted the topic ALN. Table 8.3 depicts the details of the LPs constructed by both the teachers and our system based on the middle resolution of TKM. The bolded line is the system selected learning path in middle resolution. While the rest 10 lines are teacher selected learning path. As shown in the table, although some of the teacher selected topics are the same as the ones recommended by our system, indicating that teachers are able to pick some important topics, the LP importance of their constructed LPs are lower than the system recommended one.

Figure 8.8 compares the LP importance of the LPs generated by the teachers and our system when different resolutions of the TKM are made available. In the figure, the left *y*-axis shows the LP importance and is referred by the histogram, while the right *y*-axis shows the LP importance ratio of the manually selected LPs w.r.t. the system recommended one and is referred by the polylines. We group the results by the resolutions of the TKM. It is found that no matter which resolution of the TKM is made available, our system still produces LPs with a higher LP importance than the teacher generated ones. The upper and the lower polylines respectively show the maximum and the averages of LP importance ratios of the teacher generated LPs. They indicate the quality of the LPs generated by the teachers w.r.t. to the system recommended ones. On the other hand, when the resolution of the TKM increases, the generated LPs both by the teachers and our system also increase in the LP importance. It is because when richer course domain information is made available, i.e. more association links forming the TKM, a better decision can be made on the LP construction. However, as teachers are generally overwhelmed by the massive number of LRs and association links, they tend to construct LPs based on partial information from the TKM. As a result, their produced LPs are of lower LP importance.

8.2.4.2 Comparison of Performance on Two Groups of Students

We conducted experiments on comparing student learning performance based on the teacher generated LPs and the system recommended one. We have invited 10 postgraduate students from School of Computer Science, Shanghai University, to participate the experiments. It is easier to invite students from School of Computer Science rather than students from other departments as we are in the same School, but this does not affect the experiment results, as long as these students have different learning abilities, who perform differently when studying the same LR. We randomly divide the students into two even groups. The 1st group of students perform learning based on the teacher constructed LPs, while the 2nd group of students learn by the system recommended LP. All students are given 50 min for studying the contents (contains 5 LRs) provided the LPs and take the same examination with 25 questions, which assess their understanding. Results show that

Table 8.3 Topics in the selected learning path in middle resolution

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Importance degree
Teacher 1	FDA	Roche	Avastin	Stent	Patient	9.6
Teacher 2	Antidepressant	Vaccine	FDA	Avastin	Drug	15.2
Teacher 3	Cancer	Risk	Analyst	Company	Childhood	12.8
Teacher 4	Patient	Staff	Pneumonia	Drug	Analyst	17.0
Teacher 5	Researcher	Implant	Company	Calcium	Cancer	9.2
Teacher 6	Company	Calcium	HPY	Supplement	France	11.2
Teacher 7	FDA	Pneumonia	Dialysis	Antidepressant	treatment	12.2
Teacher 8	Cancer	Implant	Test	Screening	Prostate	7.2
Teacher 9	Analyst	Pharmaceutical	Medicine	Company	Premium	11.2
Teacher 10	**Antidepressant**	**Patent**	**Pneumonia**	**Analyst**	**Staff**	**15.8**
System	Drug	Company	Avastin	Pharmaceutical	Shortage	27.2

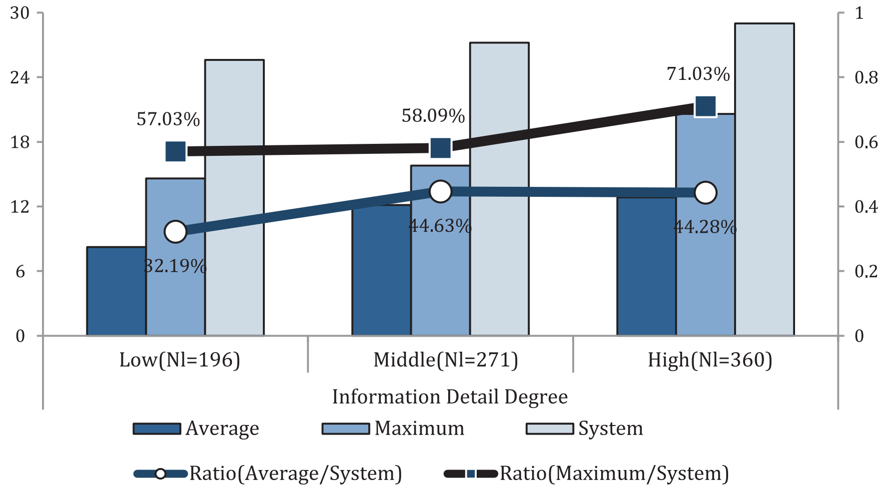

Fig. 8.8 Comparison of manually selection and system recommendation results of learning path in learning resources ALN in terms of importance degree

students using the system recommended LP perform better and have more stable learning performance.

Better Learning Performance

We compare the learning performance of two groups of students on the LRs using two-sample *T*-tests on the differences of their learning performance as in Eq. (8.1).

$$t = (\overline{x_1} - \overline{x_2}) / \left(s_{x_1 x_2} \cdot \sqrt{2/n} \right) \tag{8.1}$$

where $\overline{x_1}$ and $\overline{x_2}$ are the means of their performance within the first group and the second group respectively on n LRs, and $s_{x_1 x_2}$ is the standard deviation of the two samples. $\overline{x_1} - \overline{x_2}$ is the standard error of the difference between the two means. Assuming the null hypothesis is that the two groups of students have the same learning performance on the same LRs. The two-sample *T*-tests are used to determine if the two groups of data are significantly different from each other. In practice, we can directly use the function of "*T*-test" in Microsoft Excel software to automatically calculate the t value. Its value is 2.50411, so the corresponding p-value is 0.0367 which is smaller than the threshold of Statistical significance (0.05). It means the null hypothesis is rejected, i.e. the learning performance of the two student groups is significantly different. We then compare the detailed learning performance of the two student groups based on each LR. As shown in Fig. 8.9, students studying using the system recommended LP generally perform better. In average, they got 60.8 % in the examination, while the students studying through manually selected LPs got 51.2 % only. Note that y-axis shows the scales of the learning performance, while x-axis shows the indices of individual

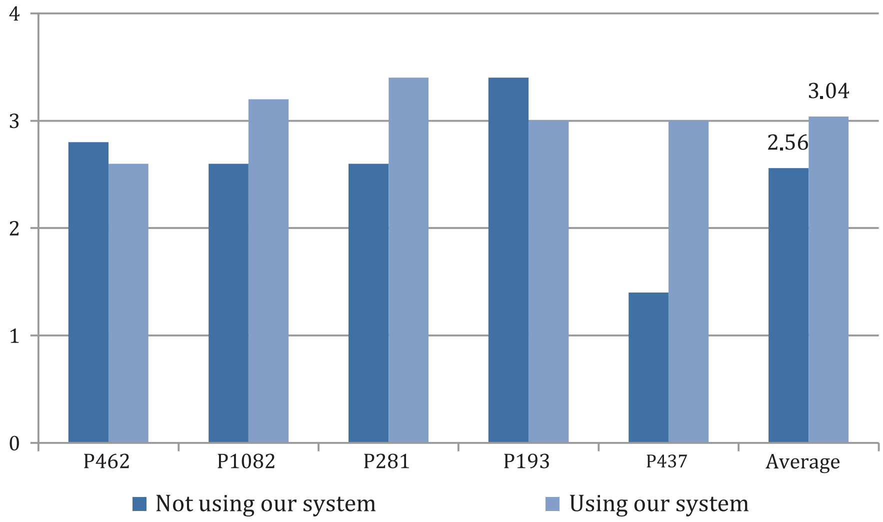

Fig. 8.9 Comparison results of two types of learning

LRs. Although students using the system recommended LP perform less well in LRs P462 and P193, learning performance of both student groups in such LRs are still quite similar.

Stable Learning Performance

We test if the students in each group can have similar learning performance σ_i^2 on the same LR i by analyzing their performance variances (ref. Eq. 8.2). The results are shown in Fig. 8.10, where the y-axis indicates the performance variances.

$$\sigma_i^2 = 1/m \cdot \sum_{j=1}^{m} \left(x_{ij} - \bar{x}_i\right)^2 \tag{8.2}$$

where σ_i^2 is the performance variances of LR i, $\bar{x}_i$ is the average performance on LR i, x_{ij} is the learning performance on LR j of student x_j, and m is the number of students If different students show similar learning performance on the same LR, their learning performance variances will be low. We refer this as stable learning performance. For instance, if all students have the same learning performance on the same LR, the performance variance will be equal to 0, and their learning performance is the most stable. In contrast, if half of the students got very high marks and the other half got very low marks, their learning performance is described as unstable, where the performance variance can approach to 6 according to Eq. 8.2.

As shown in Fig. 8.10, although students studying through manually selected LPs (Group 1) perform slightly better on LRs P462 and P193 than those studying by the system recommended LP (Group 2), the learning performance of group 1 students is quite unstable, i.e. students perform quite differently in the same LR. Overall, group 2 students generally have more stable learning performance than

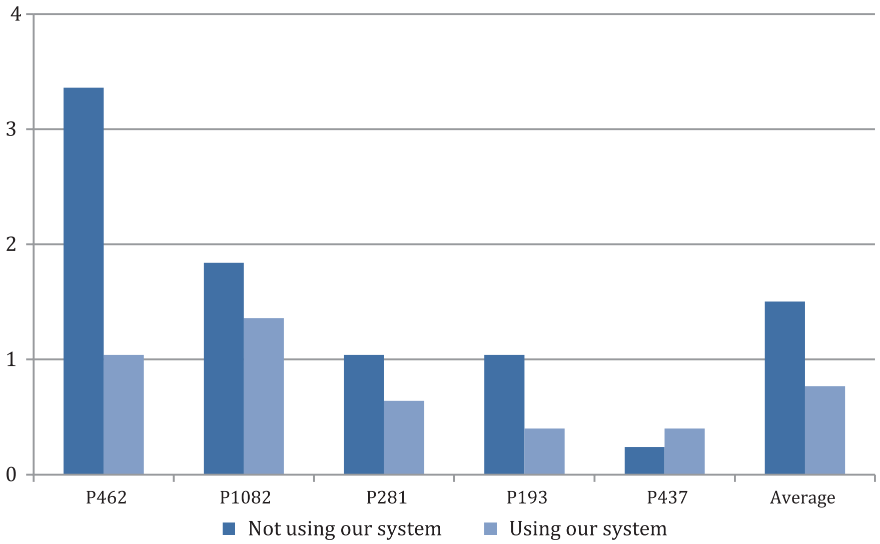

Fig. 8.10 Comparison of students' stability of learning performance

group 1 students. However, for LR P437, group 1 student has more stable learning performance as they have consistently low performance in such a LR. Our experiments indicate that by using the system recommended LP, even student coming with different learning abilities can be trained to perform better in learning. In addition, the entire cohort will have a more stable learning performance.

8.2.5 Summary

In this section, we have presented an ALN-based LP construction method. We construct multi-level of abstractions of LRs through association, allowing a knowledge map like LP to be derived. Such a LP structure can help students to learn more effectively. The ALN-based association structure also allows important parameters of LRs, such as their complexity and importance, to be derived. This offers sufficient information for automatic construction of pedagogically meaningful LPs. This feature is particularly critical when a massive amount of Web resources are considered to be transformed as LRs for students to learn.

We have implemented all the above features of the ALN-based LP construction method in an application program programmed by Java. We kept all the data of LRs in text files which are downloaded from www.reuters.com by a Web crawler. We use JSP (JavaServer Pages) to compile the web pages. The interaction between the application program and the user interface is connected through the Web Service. We use Tomcat as the web server to run the JSP Pages. Our experiments show that our method offers better and much stable student learning performance.

In practice, as Web resources obtained from different providers may have very different presentations and inconsistent contents.

8.3 Implementation for Fuzzy Cognitive Map Based Student Progress Indicators

To answer the third research question of how well students have learned, which requires finding out student learning progress, learning qualities, and student potential to maker further improvements, we have proposed Fuzzy Cognitive Map based student progress indicators. In order to verify this method, we have collected academic data of high school students and applied our student progress indicators to the analysis of their learning progress. And also, we designed questionnaires for both teachers and students by providing them the learning progress analysis results and ask if they understand and agree with the learning progress results.

8.3.1 Instrument (Questionnaires)

To verify this research work, we evaluate if the proposed Fuzzy Cognitive Map based student progress indicators can help both teachers and students to better understand student progress and provide them more information to manage the teaching and learning process. This research work collects feedbacks from teachers and students using questionnaires and generates graphs to visually describe student progress.

These graphs present student progress in different learning stages, show how the performance on an attribute affects the performance of the other attributes, compare the performance among different groups of students, and also indicate the potential of students making progress in the future.

We designed two kinds of questionnaires for teachers (Appendix B) and students (Appendix C), respectively. Both of them contain six questions which evaluate the visualized learning progress in six aspects that covers different stages of learning from Early stage, Interim stage, to Mature stage. These questions aim to collect if teachers and students can better understand student progress and make the learning process more efficient.

8.3.2 Participation

In order to analyze student learning progress with our Fuzzy Cognitive Map based student progress indicator, we need teachers' help to set the learning outcomes for each subject, and also we need to collect student learning performance according to their learning outcomes. We ask 6 teachers in 6 subjects to set learning outcomes in terms of the performance related attributes and non-performance related attributes. And also, we have collected academic data of 60 students from No. 83 High school of Xi'an, China. The same teachers and students are required to evaluate our work by determine if the student progress analysis results can help them to better understand student learning progress and make further improvements.

8.3.3 Data Analysis

When teachers and students try to understand student progress, it is greatly straightforward to let them visualize the learning progress. If analysis results can be presented in the form of graphs, we can design a visual questionnaire and use quantitative answers to respectively collect evaluation results from teachers and students.

Graph Comparison: We have collected a great number of data about student learning progress, including the values of performance-related attributes and non-performance related attributes at different learning stages, the performance and development balance degree on a variety of subjects for different groups of students, students' potential for making progress, the changes of students' performance over different tests, and the impacts of attributes on the performance of other attributes. It is not sufficient to use only numeric analysis to present the comparison of learning progress that changes with different attributes, different learning stages, different groups of students, and different tests. We used graphs to present the comparisons of all of them in order to help both teachers and students to better understand students' learning progress.

Likert Scale: we also collected both teachers' and students' evaluation results regarding the analyzed student progress via questionnaires. To quantify their evaluation results, we applied 5-point likert scale to collect data. Similarly, each question has 5 options (Totally Agree = 5, Agree = 4, Neutral = 3, Not Quite Agree = 2 and Disagree = 1).

8.3.4 Evaluation

Besides involved in our experiments, the teachers and students also helped evaluating our method by answering questionnaires. These questionnaires show the results of student learning progress generated from our method. Teacher's questionnaire shows the overall learning progress and the progress of different groups of students. And students' questionnaire shows individual student's learning progress and the group progress of the student belongs to. Because these students and teachers are Chinese, so the questionnaires are conducted in Chinese as shown in Appendix B (Analysis results for teachers) and Appendix C (Analysis results for teachers). Both teachers and students evaluate our results mainly from the aspects of if the results coincide with their cognition and can help them to better understand the learning progress. We have asked them opinions on our 6 parts of experiments (P1–P6). P1, P2 and P3 concerns results describing the early, interim and mature stages of study. P4 concerns student progress over time. P5 concerns student grouping. Finally, P6 concerns the strength of impact of each attribute for different groups of students. We respectively asked opinions from teachers and students about how accurate our experiment results explain student learning performance and how good our results in helping students to understand their learning performance and make improvement. We used a Likert-type scale with scores from 1 to 5 in each of the questions P1–P6. Scores 1–5 means totally disagree, agree with a small part, agree with half of the experiment results, mostly agree, and totally agree, respectively. Based on the scores obtained, we normalized them within the range of [0, 1] as shown in Fig. 8.11 to intuitively illustrate the level of agreement by teachers and students. As shown in Fig. 8.11, the average score 0.74 shows teachers mostly agree our results explain student learning performance accurately. Specifically, as shown in Fig. 8.11b, such level of agreement applied to both teachers of the Science and Arts subjects as they got almost the same scores. Figure 8.11c shows opinion from students. Results show that students had a very high level of agreement (scored 0.86 in average and scores of P2 and P6 ≥ 0.9) that our results well depicted their learning performance and could help them to make improvement.

8.3.5 Summary

We have developed student descriptors, which are formed by SAM, PPF and FCM to mathematically model both students' PAs and NPAs, the changes of these attributes over time and their causal relationship. This supports comprehensive student progress analysis. We have also developed student progress indicators to pedagogically depict student progress and development in both individual and group of students setting, and also show such information against the teacher's expectation. We have conducted experiments with 60 students and have disseminated information on student progress and development based on our method. Our evaluations show that both the teachers and the students mostly agree that our method can well explain student progress and development, and the information that we depicted can clearly illustrate how a student can make improvement. As a future work, we are now working on visualization methods to help disseminating student progress and development in a more intuitive way.

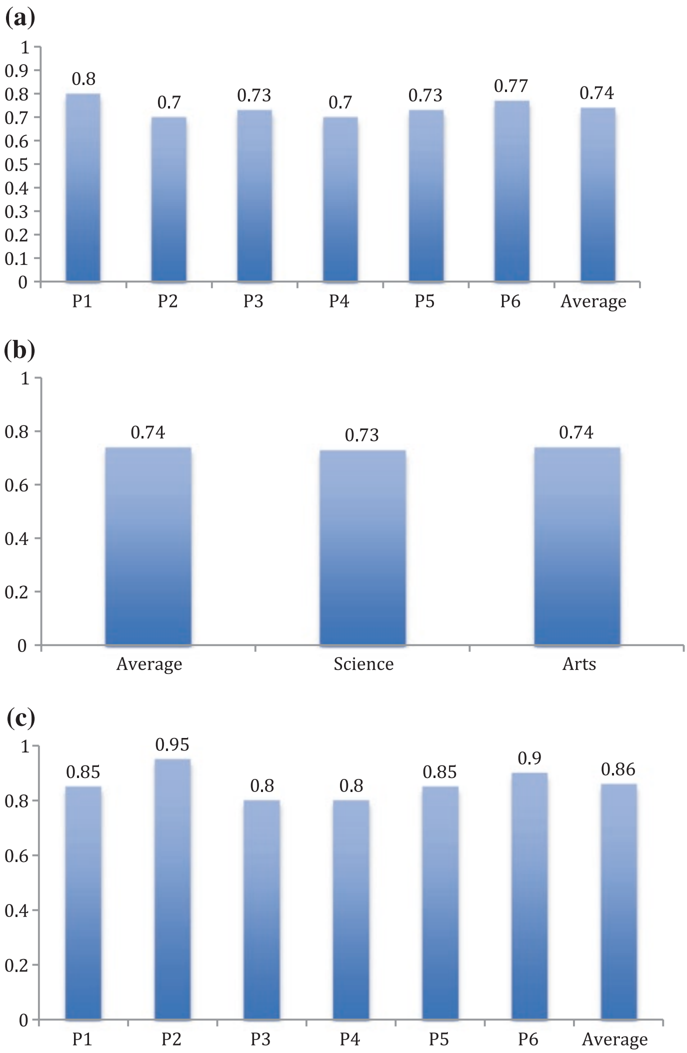

Fig. 8.11 Evaluation results. **a** Teachers' opinion. **b** Subject teachers' opinion. **c** Students' opinion

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Chapter 9
Conclusion and Prospect

9.1 Introduction

This monograph focuses on developing methods for constructing learning paths in terms of “learning resources,” “learning approaches,” and “learning quality” to support student learning. To find out a model that helps teachers to design teaching approaches, we define different teaching approaches for learning activities and organize them into a learning path which indicates the learning sequence of different learning activities. And to find out the appropriate learning resources, we automatically generate well-structured learning resources from loosely connected Web resources. These learning resources are delivered to students, who have different knowledge backgrounds, learning interests, and knowledge levels, to study knowledge. In the end, to provide methods to help teachers and students to determine student learning quality in a more intuitive way, we evaluate student learning performance to analyze their learning progress using the proposed student attribute descriptors and student progress indicators.

9.2 Research Contribution

9.2.1 A Fine-Grained Outcome-Based Learning Path Model

Existing methods generate learning paths based on attributes that describe learning contents and student learning performance. However, these content-based works do not properly incorporate the teaching and learning approaches. As a result, the learning outcomes are assessed by the mastery levels of learning contents. However, it is hard to assess other forms of learning outcomes, such as generic skills. In addition, the learning activities only provide simple forms of teaching methods that make them hard to be defined and reused for another courses.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9_9

We have proposed a fined-grained outcome-based learning path model, which provides a learning path construction method to design the components of the learning path and to change the setting of these components based on learning outcomes. The proposed model allows the assessment methods open to different types of learning outcomes, supports different teaching approaches to different types of courses, and also students can obtain more comprehensive guidance.

Our outcome-based learning path model incorporates the Bloom's Taxonomy [Bloo56] for learning path construction to support more precise learning outcome assessment. In fact, the proposed model is also open to different types of learning outcome assessment methods and inference algorithms [Cona02, Chen06]. This feature allows an ITS that is built on top of our learning path model to easily incorporate specific subjects and even a combination of methods for evaluating student learning performance more accurately and comprehensively.

The proposed model offers an adjustable fine-grained learning activity formulation to support the implementation of different teaching approaches in a learning path. This also enhances the modeling of KEs to allow a KE to be delivered and assessed in different ways.

In the proposed model, the components of a learning path have relationships and constraints among each other. This simplifies the implementations of learning path construction systems. We also implement a prototype to display our system, and ask experienced teachers to use it and evaluate our model. In the user study, our model displays excellent functionalities that teachers with different knowledge backgrounds and different teaching experiences have shown their great interests, saying our model is useful and helpful to design learning path and to guide student learning.

According to the discussion above, the fine-grained outcome-based learning path model fulfills the research objective of finding out the teaching approaches and answers the question of how to learn, so that teachers can provide different teaching approaches for different courses, which can evaluate different types of learning outcomes including both subject-specific knowledge and skills as well as generic skills.

9.2.2 Learning Path Construction Based on Association Link Network

The learning resources are not easy to manually create, especially when designing for different students. Reusing Web resources to form learning resources offers a way for rapid course construction. However, the challenges are how to identity the properties of the Web resources, including the relevance, importance, and complexity, etc., and how to find out the relationships among them, especially, how to find out tailored learning resources for different students with different learning abilities and knowledge backgrounds, etc.

To address these problems, we proposed an Association Link Network-based learning path construction method to automatically find out the personalized learning resources according to students' knowledge backgrounds, learning preferences, learning abilities, etc. This method can automatically construct well-structured learning resources from loosely connected Web resources as teacher knowledge model. The learning path is extracted from teacher knowledge model, which contains three abstraction levels, i.e., keyword, topic, and learning resources ALNs. The learning path with three abstraction levels provides more information about the relationships among knowledge, which can help students to better understand the knowledge. Also, the method comes with a test generation scheme which can automatically generate tests and assess student understanding against learning resources.

In the ALN-based learning path construction method, we apply Association Links Network to form teacher knowledge model which identifies the associations among unorganized Web resources. Given the mass Web resources, even if we have no idea about their knowledge domains, concept structures, or learning outcomes, we still can structure the knowledge via the model. It can provide a very efficient way to organize Web resources rather than ask teachers to manually create learning resources.

Our system incrementally extracts adaptive learning path from the teacher knowledge model, which automatically converts the LRs into associated UoLs as the learning path with a set of three different ALNs. The learning path also has three abstraction levels. Any node in an ALN also can be respectively mapped to some other nodes in the other two ALNs, so that students can have more information to understand knowledge concepts with the help of the associated nodes of knowledge concepts.

We construct a test generation scheme to automatically assess student understanding against a LR within a UoL. We use the associations between topics or keywords as the rules to test if students can build up the correct association between major concepts. This automatic scheme saves a lot of efforts than manually designed tests. In the end, two comparison studies are designed to demonstrate that students using a system-recommended learning path can have better and more stable learning performance than using manually selected learning path by a teacher.

As the discussed above, the proposed ALN-based learning path construction method fulfills the research objective of automatically finding out the appropriate learning resources to construct personalized learning path which helps students to better understand the knowledge and achieves their learning outcomes.

9.2.3 Fuzzy Cognitive Map-Based Student Learning Progress Indicators

Existing works on student learning progress mainly identify student learning progress as a set of state changes made by a student regarding certain learning attributes and whether the student meets with the teachers' expectations. However, such progress information is quite primitive. It is not sufficient to form indicators to help students and teachers to make improvements on learning and teaching, unless they pay extra cognitive efforts to manually extract more comprehensive learning progress information from the feedbacks. It is because learning attributes are not independent but may have certain causal relationships among each other, which can also be dynamically changing over time. In addition, at different learning stages, student learning progress may be governed by a different set of learning attributes. For example, a student may be expected to mainly train up with concept memorization at an initial stage rather than focusing on the ability of applying knowledge. However, the situation becomes the opposite when a student is going through a mature learning stage. On the other hand, a teacher may need a higher level of student learning progress information, such as the performance distribution within a cohort, the portion of students meeting the teachers' expectations, or whether a student or a group of students is/are developing certain learning skills, to support teaching approaches adjustment.

Our work is developed to provide a comprehensive solution to address such complicated needs. We proposed Fuzzy Cognitive Map (FCM)-based student learning progress indicators, which collect student performance on student performance-related attributes and nonperformance-related attributes, analyze how their performance is changing and what factor can cause the changes of performance on certain attribute, categorize students into different types according to their different learning progress, and also propose a progress potential function to predict student learning performance in the future.

We propose a student attribute matrix to formulate all levels of both performance-related attributes and all aspects of nonperformance-related attributes. In the student attribute matrix, the row vector represents one kind of student attribute and the components in the vector represent quantified values of attribute levels. It is easy to measure student progress from different perspectives of student attributes. On the other hand, it supports the fuzzy property that a student may stay in two or more levels according to different cases. It is better to formulate a nonlinear function to calculate the effect of one attribute on one another. With the student attribute matrix, we also can group students together by one of these attributes or by a selection of attributes.

FCM is used to infer the causal relationships among student attributes which behave as the concept nodes in the map. With the FCM, we can analyze the learning behaviors of a single student, or a group of students with similar attributes. More importantly, it can analyze the factors that affect student learning progress, and describe the causal relationships among these factors, i.e., how a factor affects each other in terms of student learning progress.

According to the discussion above, the proposed student learning progress indicators fulfill the research objective of improving the learning quality and answering the question of how well students have learned. Teachers can adjust teaching approaches and try to help students to have a balanced development to handle different learning environments.

9.3 Limitations and Prospect

The outcome-based learning path model currently formulates a representation of a learning path. Basically, we can prepare learning path templates to best fit with each type of students, so teachers do not need to manually create the learning path. However, it still cannot automatically construct a learning path. Because it has to depend on teachers to manually adjust the requirements and learning outcomes of each learning activity as well as the sequences among them. These adjustments will cause a lot of extra work for teachers. And on the other hand, teachers cannot clearly know every student's learning status, so the adjustment may contain some errors. As a future work, we will work on some automatic algorithms for managing and adjusting the learning outcomes and the delivery of learning activities, based on which we plan to develop an adaptive E-Learning system.

In order to find out appropriate learning resources, we construct learning resources directly from the Web resources and identify the attributes of these learning resources to suit different types of students, and also we can make sure there is no similar learning resource exists in the teacher knowledge model. However, the selected learning resources in a learning path are obtained from different websites and created by different authors, their formats/styles of describing knowledge and skills are not consistent enough for students to smoothly obtain knowledge. Students may get confused if the contexts between learning resources are not well connected, or if the learning resources use different symbols to express the same terminology, etc. All of these deficiencies will affect students' understanding. It is necessary to find out a way to improve the consistency of the learning resources. As a future work, we will investigate methods to address such presentation and consistency problems, in order to allow students to learn more smoothly with the Web resources constructed learning materials.

Student learning progress can provide dynamic information about how students' performance on some attributes is changing, such as how student learning performance is changing over a particular attribute, predicting a student's learning performance according to the student's previous performance as well as peers learning performance, etc. However, our work only shows limited perspectives of student learning progress. On the other hand, teachers from different knowledge disciplines may be interested in different perspectives of student learning progress. They may feel some of the progress we have provided is not very useful for their teaching. If we can provide them a progress customization tool where they can customize their interested learning progress, then it will improve their teaching quality a lot. Also, if the dynamical learning process and various perspectives of student learning progress could be visual to teachers and students, they would better understand student learning progress, so that students can enhance their learning, and teachers can adjust their teaching approaches accordingly. As a reference, we could use the visualization tool [Gource] not only to present the progress across different stages, to show student learning performance in multi-resolution, but also to present the relationship among different types of attributes.

9.4 Conclusion

This chapter summarizes our works presented in the monograph, highlights the contributions including the proposed methods, the advantages, and how they achieve the research objectives, discusses the limitations of the works and the future works to overcome the limitations. This monograph has proposed a fine-grained outcome-based learning path model, which teachers can use to design learning tasks, learning activities, and learning path for different types of students. This monograph also proposed a learning path construction method which can automatically generate learning resources from loosely connected Web resources. This monograph proposed a FCM-based student progress indicator to analyze and present student progress and to find out the factors that may affect student learning performance. The future work depicts possible directions of this monograph. The future improvements of the work include automatically adjusting the components and their settings of the outcome-based learning path, presenting the learning resources in a consistent format, and designing a more effective way to visually present student learning progress. If such research work can be successfully done, more contributions on constructing learning path will be achieved.

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[Gource] http://code.google.com/p/gource/

Appendix A

Questionnaire on Learning Progress Scheme

Covering Letter

This study is organized by Miss Fan Yang, a PhD student in the School of Engineering and Computing Sciences, Durham University, who is working on a research project in e-learning.

Project Introduction

Learning path construction is a complicated task, which involves formulating and organizing activities, defining ways to evaluate student learning progress and to match such progress with designated learning outcome requirements. Our project proposes a mathematical model to formulate learning paths and learning activities. This model can lead to the implementation of a generic system to support learning path design for teachers from any subject disciplines. We have developed a simple prototype based on this model and are now conducting this user study to evaluate our work.

Abstract of the Questionnaire

The results of this study will determine whether our system can provide a convenient environment for you to design a course in terms of its learning path, track student learning progress, evaluate their performance, and provide feedback to help students enhance their learning quality.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9

Note that at this stage, the design of our prototype e-learning tool focuses only on its functionalities, i.e., generating learning paths and evaluating student progress and learning outcomes, rather than focusing on the user interface design.

Other Information

If there are questions about particular items, simply respond: "Just answer the question as you interpret it."

You will not be identified by name. All information provided by you will be treated as strictly confidential.

Your participation would help us confirm the importance and usefulness of our research on designing personalized learning path for different students.

If you have any problem, please feel free to contact me.

E-mail: fan.yang2@dur.ac.uk

Mobile: 07594324631

Department: School of Engineering and Computing Sciences, Durham University

Your participation is very much appreciated and will allow us to focus on critical issues related to control student learning progress and evaluate learning outcomes.

The questionnaire should only take less than 10 min. to complete. Could you please return it by 10 June 2010?

Questions: (19 questions)
It is recognized that teachers are likely to respond quite differently to the enclosed questions. Please answer all the questions in such a way as to reflect most clearly your viewpoints.

There is no right or wrong answer. Answer the questions in the order in which they appear on the paper. Most questions will require you to circle your selected response. Others will require you to write down a few words. Do not leave blanks.

We thank you for your contribution to this important research.

1. What's your subject?

   ☐ Science
   ☐ Art
   ☐ Engineering
   ☐ Other, please specify

2. Do you have any experience of using e-learning tools?

☐ Yes.
☐ No, but I know what it is.
☐ No, I have no idea about it.

3. How many years of teaching experience do you have?

☐ 0–1 year
☐ 1–3 years
☐ 3–5 years
☐ More than 5 years

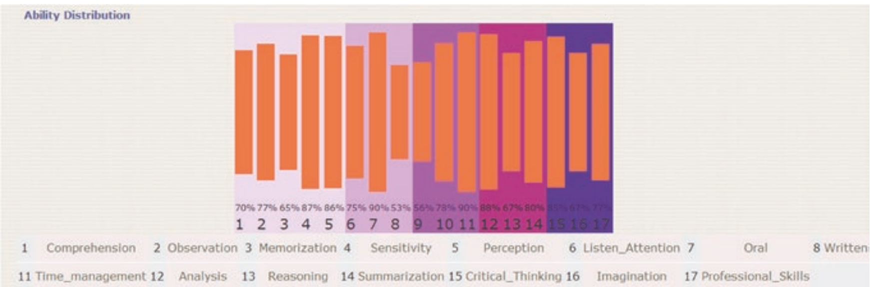
4. Do you have any experience of designing/modifying teaching materials? If yes, how do you design/modify teaching materials?

☐ No.
☐ Yes, I design/modify my teaching materials by hand.
☐ Yes, I design/modify my teaching materials with professional software. Please specify what kind of software are you using: ______________________________.
☐ Yes, I use others. Please specify: ______________________________.

5. When you design your teaching materials, you need to define student learning outcomes. How do you find the criteria to define student learning outcomes?

☐ Subject area
☐ Difficulty level
☐ Skill set
☐ Others:______________________________.

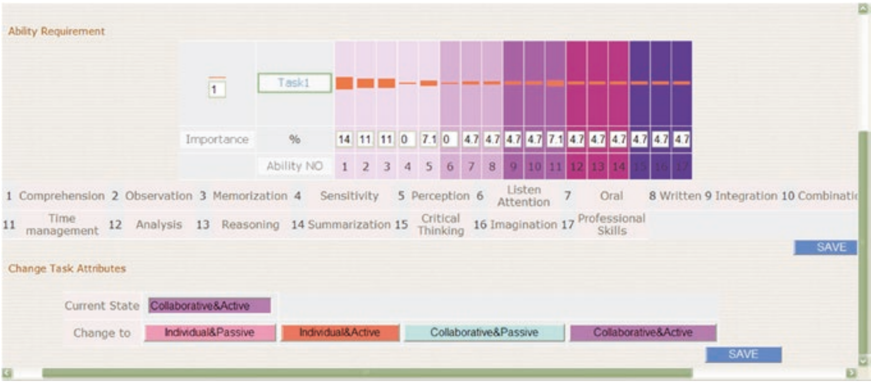
6. Student ability refers to a set of attributes describing how a student has been trained up while studying a subject area. These attributes may indicate whether a student can only recall the subject content or can apply subject knowledge to solve problems in unseen situations, for instance.



An example of a student ability table:
Teacher can use these abilities for assessment and put them to a student ability table. How will you rank the usefulness of the student ability table?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

7. To support a more fine-grained formulation for describing the learning processes of knowledge elements, we propose the idea of learning task, which is simple in nature and is designed for training up a student with a certain abilities in the way they prefer, including individual or collaborative and active or passive.



An example of a single learning task:
How do you find this idea will help you design what a student needs to learn?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

8. We divide an activity into tasks help a teacher have a better understanding on how to create/organize the activity. As somehow, a task is more closely related to abilities, so it is a bridge between an activity and a set of abilities. For example, a "lecture" activity may include "delivering bookwork type of materials" task for training up the student comprehension skill, "question–answering" task for testing out the student understandings.

Divide an activity into several tasks:
Do you think this will help you have a better picture on why the student needs to create an activity and how this activity can help a student to make progress/ to improve the student's abilities?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

9. When designing a course, it is typical for a teacher to establish a set of learning activities, such as lecture, tutorial, or practical, to support students learning different knowledge elements. Teacher is expected to put together a list of learning tasks to form the basis for constructing learning activities. By changing the ability requirements and task importance weights, the difficulty level of a learning activity would be changed as well.

An example of a learning activity:
How do you find this idea will help you decide the learning process and learning outcome of a learning activity?

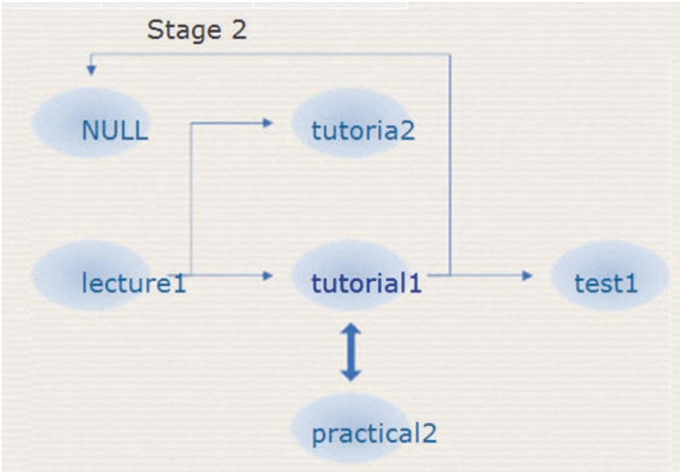
☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

10. In particular, collaborative learning activity refers to the learning activity that students are learning collaboratively in a group setting. This type of learning activity is modeled to comprise two types of learning tasks: collaborative and individual, where they are designed to be performed by a group of students collaboratively and by each individual student within a group, respectively. For example, a "Sell your Product" collaborative learning activity assigns student A an individual task "design advertisement" and assigns student B an individual task "design PPT," and each student has been assigned different individual task, but all of them should do the collaborative task together: presentation. From the student's perspective, each student typically requires to perform only collaborative learning task and the student's own individual learning task.
How do you find this idea will help you decide the idea on the group setting of a collaborative learning activity and also assess the learning outcome of a group students?

☐ Very useful
☐ Useful

☐ Not so useful
☐ Not useful at all

11. To allow a student to build up the student's knowledge progressively, it is a common practice for a teacher to divide the entire learning process of a course into a finite sequence of time slots, namely learning stages. During each learning stage, a student only needs to focus on studying a subset of knowledge elements through designated learning activities. For example, if the starting learning stage that "tutorial1" is taken place, then the student should start to learn it. And if the ending learning stage that "tutorial1" is taken place, then the student should finish learning.



An example of a single learning stage:
How do you find this idea will help you better manage the learning process?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

12. A learning path comprises a set of learning activities. There exist time constraints and dependencies among the learning activities. The starting learning stage decides when to learn a learning activity, and the ending learning stage decides when to finish a learning activity. And the time constrains also useful for verifying the coexistence dependency between two learning activities. They are useful especially when two or more learning activities are running together. For example, the ending stage of "lecture1" is the starting stage of "tutorial1," which decide "lecture1" is the prerequisite of "tutorial1." Also, "lecture1" and "practical1" share the same starting stage and ending stage, and then, both of them should be taken as the same time.

An example of a learning path:
How do you find this idea will help you better design the learning path?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

13. Learning process describes the current state of a student regarding how much knowledge that the student has been built up in a subject area. In our project, learning process can be obtained by evaluating the accumulated learning outcomes of the student across a relevant number of learning stages.
Would you find this idea helpful when you apply the results to set up rules for defining the prerequisite of a learning activity or to adjust the learning path for enhancing student learning?

☐ Very helpful
☐ Helpful
☐ Not so helpful
☐ Not helpful at all

14. We also allow different assessment methods to be incorporated for better capturing student performance or learning outcomes. Based on a well-developed theory Bloom's taxonomy, we can assess a student in three domains: cognitive (knowledge based), affective (attitudinal based), and psychomotor (skill

based). For example, Bloom's taxonomy classify the cognitive domain into six levels from easy to difficult: knowledge, comprehension, application, analysis, synthesis, and evaluation.
How do you find this idea will help you better assess a student performance?

☐ Very useful
☐ Useful
☐ Not so useful
☐ Not useful at all

15. To assess student learning outcome, we propose to use student abilities as the basis due to its practicality and the availability of the Bloom's taxonomy. A student ability-specific evaluation function can generate a score to describe the level of achievement of a student in a particular student ability. The evaluation function could be simple marking, grading, or item response theory.

How do you find this idea will be easier to assess a student performance?

☐ Very easy
☐ Easy
☐ Not so easy
☐ Not easy at all

16. Is that possible to apply our e-learning tool to in your teaching subject?

☐ All of them could be applied to my teaching subject.
☐ Most of them could be applied to my teaching subject.

☐ Part of them could be applied to my teaching subject.
☐ None of them could be applied to my teaching subject.

17. What's the biggest difference from the e-learning tools you had experienced before?
From the aspect of functionality____ ____ ____ ____ ____ ____
From the aspect of convenience____ ____ ____ ____ ____ ____
From the aspect of flexibility ____ ____ ____ ____ ____ ____ ____
From the aspect of accuracy____ ____ ____ ____ ____ ____ ____
From the aspect of understandability____ ____ ____ ____ ____ ____
Others__ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____
18. When you design your teaching materials, which aspect do you focus most? Could you provide some details how you design your teaching materials?
__ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____
____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____
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____ ____ ____ ____ ____ ____ ____ ____ __
19. Please make any further comments on the design/usage/clarity/ or suggestions for improvement of this system below.
__ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____
____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____ ____
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Appendix B

Questionnaire: Analysis results for teachers

The analyzed subjects in this experiment include math, physics, chemistry, politic, history, and English, where the first 3 subjects are science subjects and the last 3 subjects are art subjects. According to the data collected from different teachers, those teachers provide their teacher requirements according to the 3 domains (cognitive, affective, and psychomotor) that are used to measure student learning performance. Based on those requirements, we evaluate students and divide their performance into 5 scales, which are disqualified, below average, satisfactory, good, and best.

B.1 Early Stage of Learning

This stage includes several lower levels in the 3 domains (cognitive, affective, and psychomotor) to evaluate student learning performance, which are used to evaluate student in normal situation.

Cognitive: cognitive and remember, understand, application;

Affective: accept knowledge and give response;

Psychomotor: the ability of using senses to guide behavior, the preparation work before learning, and practice according to guideline.

B.1.1 Classification Results

The overall distribution results of the 60 students are shown by the following figure: (Fig. B.1) whole subjects; (Fig. B.2) science subjects; and (Fig. B.3) art subjects. The number of students in each class is represented in the brackets after the

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Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9

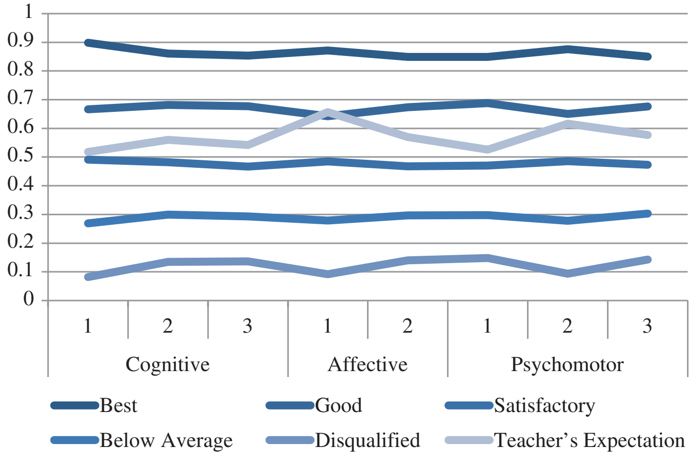

Fig. B.1 All subjects

classification. Those figures show that each class of students has stable performance in different aspects of different domains for all subjects. The basic rule is that if a student has better performance in a domain, then the student would have better performance in other domains. The same rule can be applied to science subjects (Fig. B.2) as well as to art subjects (Fig. B.3). However, (1) the 60 students has better performance in science subjects than that in art subjects and (2) the differences in science subjects are much larger than that in art subjects.

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same

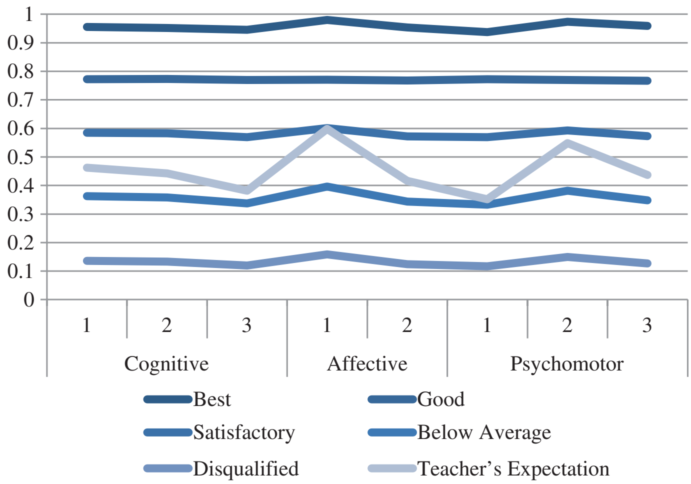

Fig. B.2 Science subjects

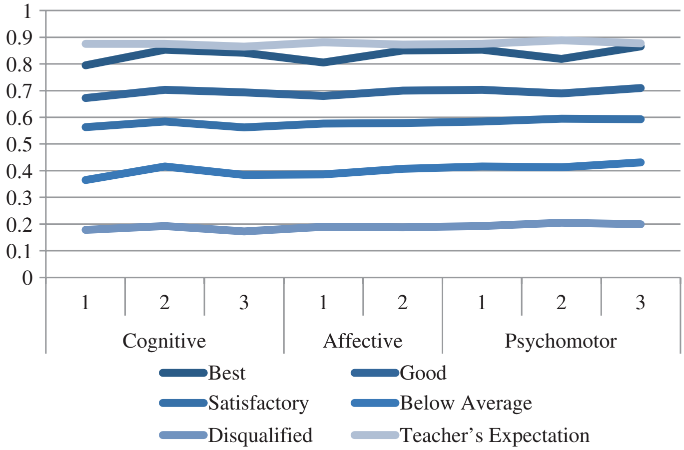

Fig. B.3 Art subjects

as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; and 5: basically the same).

B.1.2 The Relationship Between Different Attributes

We have collected the teaching requirements in the domain of cognitive, affective, and psychomotor, as well as the participation mode of students (collaborative learning or individual learning). We also collected the teaching styles of each teacher in the aspects of learning content (specific or abstract), expression (virtual or oral), information organization (inductive or deductive), participation attitude (passive or active), and teaching sequence (sequential students who learn in continual steps and global students who learn gradually from the whole knowledge structure to more detailed concepts). Actually, the change (progress or regress) of an aspect will affect the change (progress or regress) of other aspects, so we have analyzed the casual relationships between the 9 aspects according to student learning performance.

Given all subjects, the causal relationships between the 9 aspects in the early stage for the 60 students are shown in Fig. B.4, where a node represents an aspect, an arrow represents that the starting node takes effect on the ending node, and the weight for each arrow represents the relative impact of one aspect on another (0 weight means no impact and 1 weight means the impact is the largest). The figure shows that the 3 domains such as cognitive, affective, and psychomotor are taking effect on each other; i.e., progress in any domain would cause the progress in the other two domains. The balance development of student learning styles would directly affect the performance of cognitive and psychomotor. And the impact of balance degree of learning style on cognitive is larger than that on psychomotor.

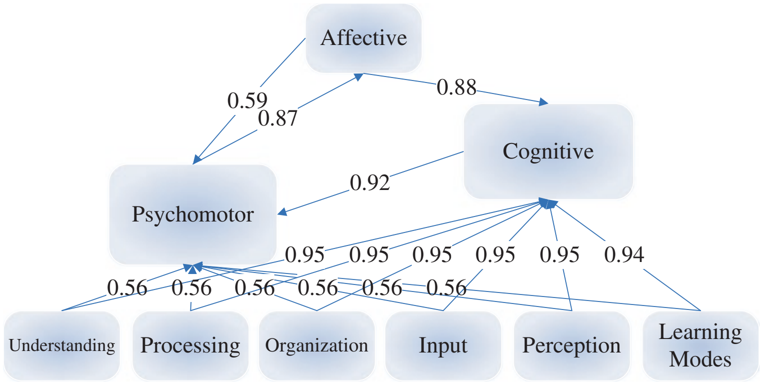

Fig. B.4 The casual relationships between the 9 aspects in early learning stage for the 60 students

Given all subjects, according to the learning performance of all students in the early learning stage, the overall impact of each aspect on the other aspects is shown in Fig. B.5. Because the early stage only measures student's basic abilities, the differences between good students and poor students in the 3 domains are quite small. In this stage, the balance degree of learning styles mainly effects the performance in other aspects. Above all, no matter for different types of students, or for different subjects, the casual relationships between those aspects are quite the same, and only the impacts have small differences.

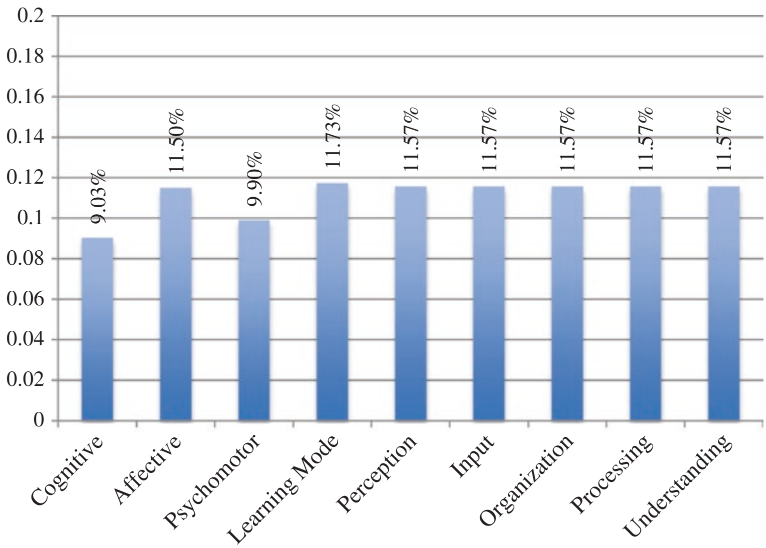

Fig. B.5 The overall impact of each aspect on the other aspects according to the learning performance of all students in the early learning stage

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; and 5: basically the same).

B.2 Interim Stage—Potential of Making Progress

This part analyzes the potential of making further progress. If a student does not only has good performance in the 3 domains, but also can develop his learning styles balanced according to different teaching modes, then the student has the potential of making progress and has stronger ability of self-learning. For this type of students, no matter how difficult the learning activities are, or using which way of teaching, they all can have good performance. On the contrary, for the students having "low potential of making progress," teachers should teach them in terms of their learning styles. The evaluation in interim stage also indicates whether the student is making progress in the right direction.

The following 3 figures are the analysis results of learning performance in the 9 aspects for all subjects, science subjects, and art subjects, respectively. For each figure, the horizontal axis represents student ID, the left vertical axis represents their relative performance (0: the worst and 1: the best), and the right vertical axis represents their classification level (1: the worst and 5: best). The 3 curves in the figure are the overall performance of student potential in the 3 domains and the balance degree of learning styles, respectively. Generally speaking, no matter for which type of subjects, if a student has better overall performance in the 3 domains, then he has better balance degree of learning styles, which means that he has larger potential to make progress. There are also exceptions; for example, student S15 belongs to best students and student S2 is just a good student. However, the balance degree of S15 is lower than that of S2 (Fig. B.8). But for different types of subjects of a student, he has different performance in the 3 domains, his balance degrees of learning styles are different and the corresponding potentials also have differences. For example, for all subjects and science subjects, student S2 (marked by black in all figures) belongs to best according to his performance in the 3 domains (Figs. B.6 and B.7); however, his performance in art subjects is only good (Fig. B.8).

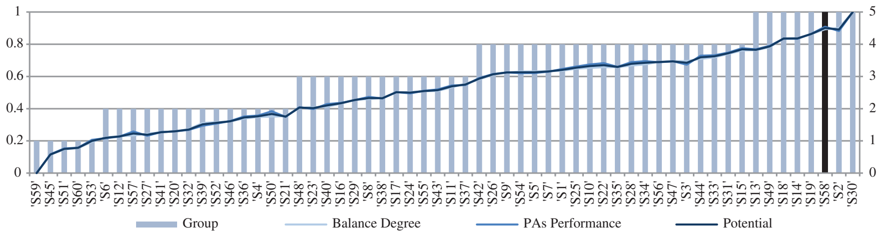

Fig. B.6 All subjects

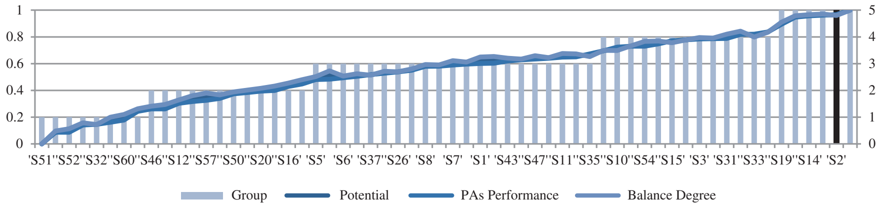

Fig. B.7 Science subjects

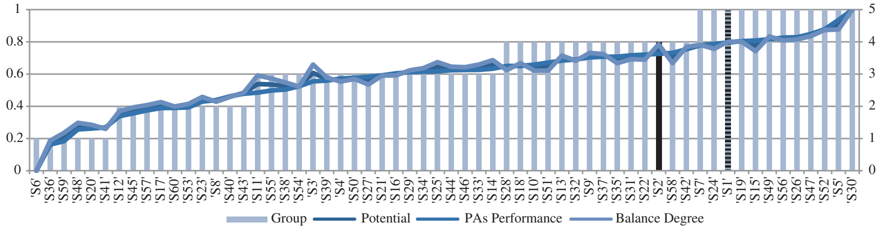

Fig. B.8 Art subjects

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; and 5: basically the same).

B.3 Mature Stage

This stage includes lower levels and higher levels of the 3 domains (cognitive, affective, and psychomotor) to evaluate student, which is especially used to tell the differences between best students and normal students.

Cognitive: cognitive and remember, understand, application, analysis, comprehensive, and creative ability;

Affective: accept knowledge, give response, evaluate, and organize, form sense of worth to affect behavior;

Psychomotor: the ability of using sense to guide activities, preparation work before learning, to practice according to guidance, freely apply knowledge, be good at gained skills, ability of adapting oneself quickly to changing conditions, to solve problems based on creative behavior.

B.3.1 Classification Results

The overall distribution results of the 60 students are shown by the following figures: (Fig. B.9) all subjects; (Fig. B.10) science subjects; and (Fig. B.11) art

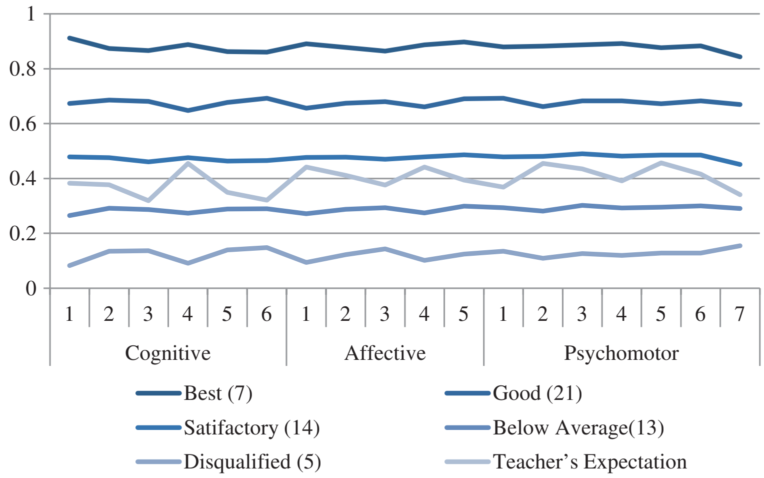

Fig. B.9 All subjects

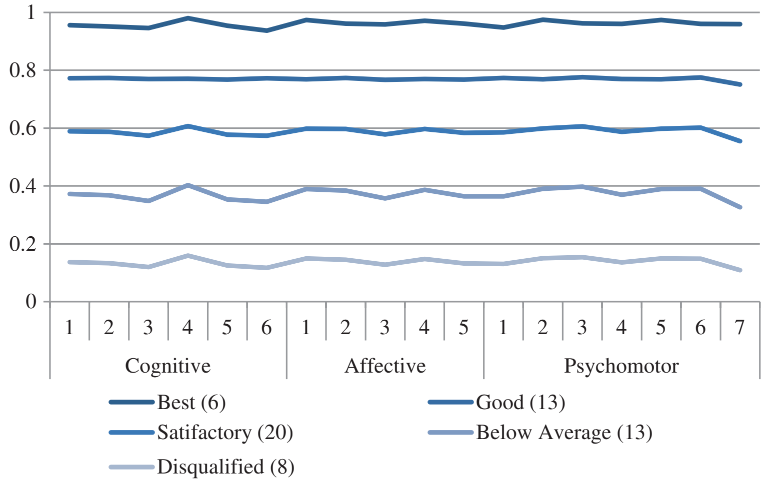

Fig. B.10 Science subjects

subjects. The number of students in each group is indicated in the brackets after that type. We can give the same conclusion as "early stage." Those figures show that for all subjects, each type of students has stable performance in different aspects of each domain. The same rule is that if a student has better performance in a domain, then the student would have better performance in other domains. The same conclusion can be applied to science subjects (Fig. B.10) and art subjects (Fig. B.11). However, the 60 students (1) have better performance for science

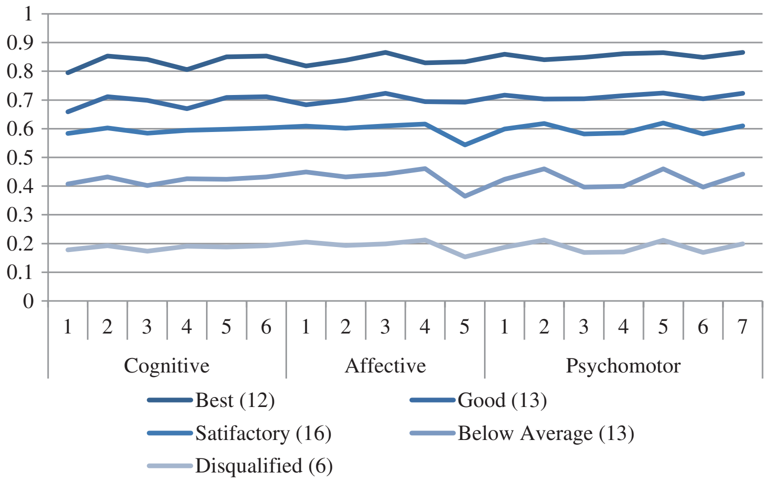

Fig. B.11 Art subjects

subjects than that of art subjects in the 3 domains, (2) and the performance differences between science subjects are apparently larger than that of art subjects. The difference is that the distribution of each type of student is a little different from that of early stage.

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; and 5: basically the same).

B.3.2 Mature Stage—Potential of Making Progress

Similar to the analysis for the interim stage, the following 3 figures are the analysis results of learning performance in the 9 aspects for all subjects, science subjects, and art subjects, respectively. For each figure, the horizontal axis represents student ID, the left vertical axis represents their relative performance (0: the worst and 1: the best), and the right vertical axis represents their classification level (1: the worst and 5: best). The 3 curves in the figure are the overall performance of student potential in the 3 domains and the balance degree of learning styles, respectively. Similar to the analysis results of early stage, the difference is that the students classification results have a little difference, where the potential of 9 students has increased, while the potential of other 8 students has decreased. Generally speaking, for the 60 students, no matter for which type of subjects, if a student has better overall performance in the 3 domains, then he has better balance degree of learning styles, which means that he has larger potential to make

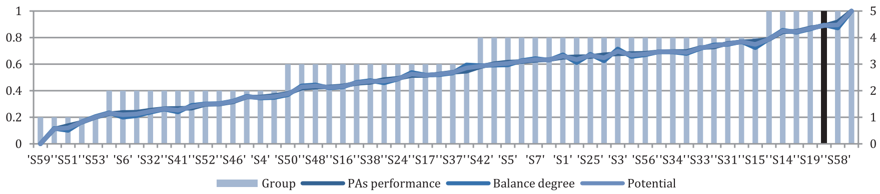

Fig. B.12 All subjects

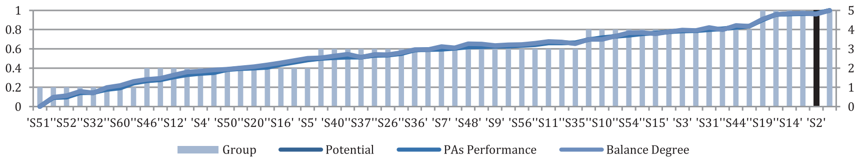

Fig. B.13 Science subjects

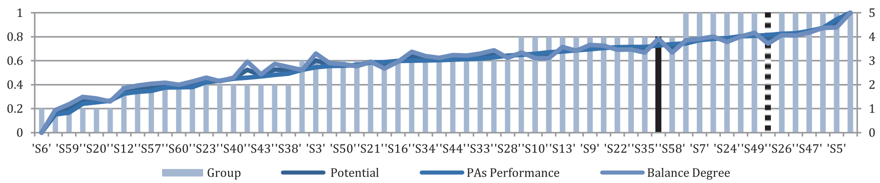

Fig. B.14 Art subjects

progress. There are also exceptions; for example, student S15 has better performance than S2 in the 3 domains, but the balance degree of learning styles of S15 is lower than S2 (Fig. B.8). But for different types of subjects of a student, he has different performance in the 3 domains, his balance degrees of learning styles are different, and the corresponding potentials also have differences. For example, for all subjects and science subjects, student S2 (marked by black in all figures) belongs to best according to his performance in the 3 domains (Figs. B.12 and B.13); however, his performance in art subjects is only good (Fig. B.14).

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; and 5: basically the same).

B.3.3 The Causal Relationship Between Different Aspects

Similar to the experiment described in section Appendix A.1.2, the changes of an aspect (progress or regress) would affect the changes (progress or regress) of the

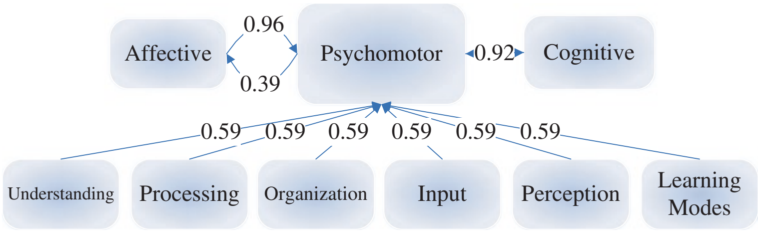

Fig. B.15 The casual relationship between different aspects according to the performance of all students for all subjects at mature stage

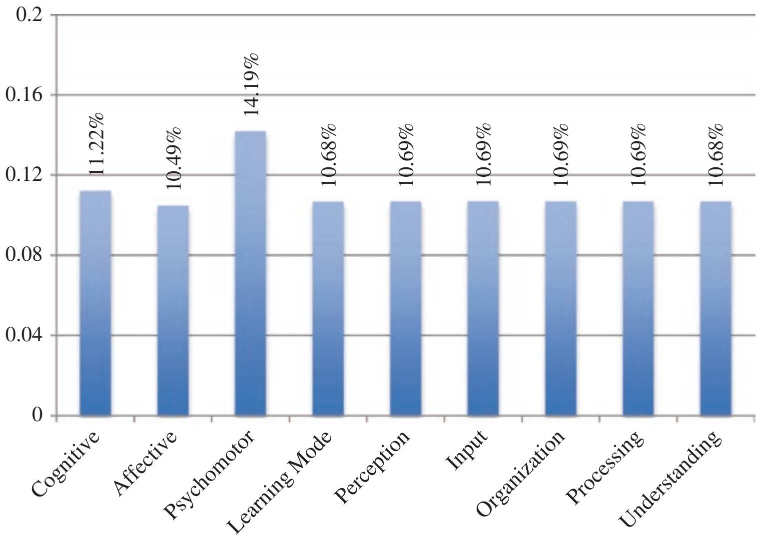

Fig. B.16 The overall impact of each aspect on the other aspects according to the performance of all students for all subjects at mature stage

other aspects, so we have analyzed the casual relationships between the 9 aspects according to student learning performance. Given all subjects, the causal relationships between the 9 aspects in the early stage for the 60 students are show as Fig. B.15. Psychomotor has become the core aspect, which affect affective and cognitive with each other. In the meantime, because of the learning styles reflecting different characteristics of learning behavior, so the changes of any aspects of learning styles can affect the performance in psychomotor.

According to the performance of all students for all subjects at mature stage, Fig. B.16 gives the impact distribution of each aspect on the other aspects. Apparently, at mature stage, student behavior has become the aspect that has the largest impact on the other aspects. Above all, no matter for different types of students, or for different subjects, the casual relationships between those aspects are quite the same, only the impacts have small differences.

According to your knowledge to the learning performance of the 60 students during the teaching and learning practice, whether the analysis results are the same as your knowledge? (Please score from 1 to 5—1: totally different; 2: partly same; 3: half is the same; 4: most are the same; 5: basically the same).

Appendix C

Questionnaire: Analysis results for student S2.

The analyzed subjects in this experiment include math, physics, chemistry, politic, history, and English, where the first 3 subjects are science subjects, and the last 3 subjects are art subjects. According to the data collected from different teachers, those teachers provide their teacher requirements according to the 3 domains (cognitive, affective, and psychomotor) that are used to measure student learning performance. Based on those requirements, we evaluate students, and divide their performance into 5 scales, which are disqualified, below average, satisfactory, good, best.

C.1 Early Stage of Learning

This stage includes several lower levels in the 3 domains (cognitive, affective, and psychomotor) to evaluate student learning performance, which are used to evaluate student in normal situation.

Cognitive: cognitive and remember, understand, application;

Affective: accept knowledge, and give response;

Psychomotor: the ability of using senses to guide behavior, the preparation work before learning, and practice according to guideline.

C.1.1 Classification Results

Given all subjects (Fig. C.1), the performance of student S2 in the 3 domains is classified to "best," and his performance in other aspects is higher than the other best students, and is much higher than teacher's expectation.

F. Yang and Z. Dong, *Learning Path Construction in e-Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-10-1944-9

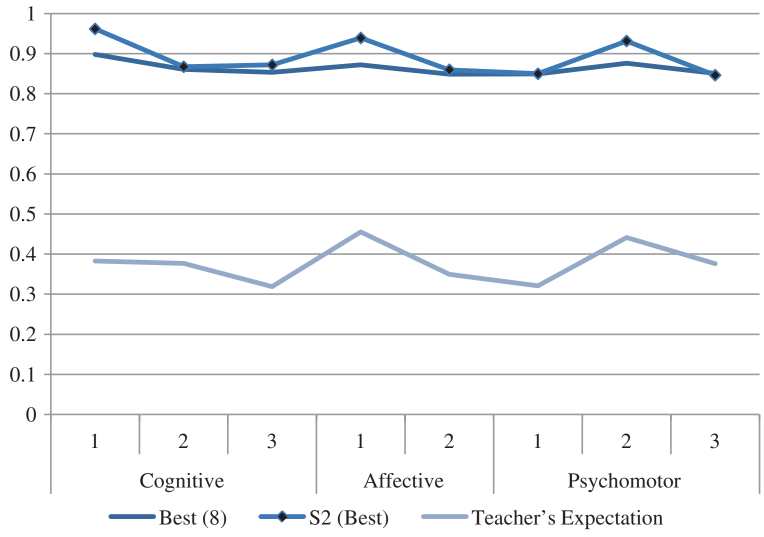

Fig. C.1 All subjects

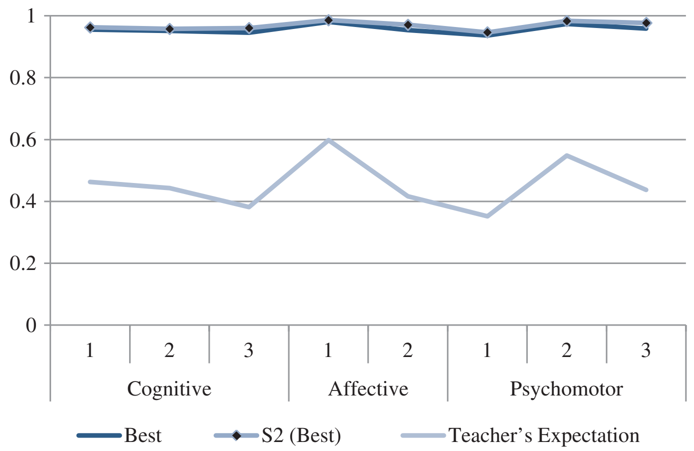

Fig. C.2 Science subjects

Given science subjects (Fig. C.2), the performance of student S2 in the 3 domains is classified to "best," and his performance in all aspects keeps the same with the other best students, and is much higher than teacher's expectation.

Given art subjects (Fig. C.3), the performance of student S2 in the 3 domains is classified to "good," and his performance in other aspects is higher than the other good students, and could be classified to "best" in some ways, at the same time, his performance is higher than teacher's expectation.

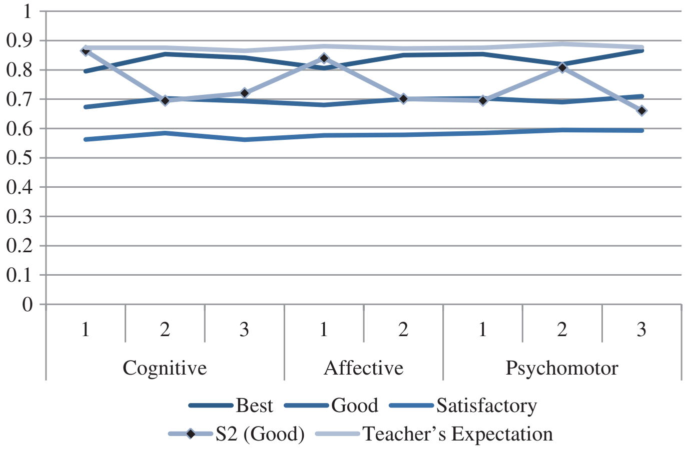

Fig. C.3 Art subjects

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know a little about my learning situation; 4: know my learning situation; 5: know my learning situation quite well).

C.1.2 The Causal Relationship Between Different Aspects

We have collected the teaching requirements in the domain of cognitive, affective, and psychomotor, as well as the participation mode of students (collaborative learning or individual learning). We also collected the teaching styles of each teacher in the aspects of learning content (specific or abstract), expression (virtual or oral), information organization (inductive or deductive), participation attitude (passive or active), teaching sequence (sequential students who learn in continual steps, and global students who learn gradually from the whole knowledge structure to more detailed concepts). Actually, the change (progress or regress) of an aspect will affect the change (progress or regress) of other aspects, so we have analyzed the casual relationships between the 9 aspects according to student learning performance.

Given all subjects, the causal relationships between the 9 aspects in the early stage for student S2 are show as Fig. C.4, where a node represents an aspect, an arrow represents that the starting node takes effect on the ending node, and the weight for each arrow represents the relative impact of one aspect on another (0 weight means no impact, and 1 weight means the impact is the largest). The figure shows that the 3 domains of cognitive, affective, and psychomotor are taking

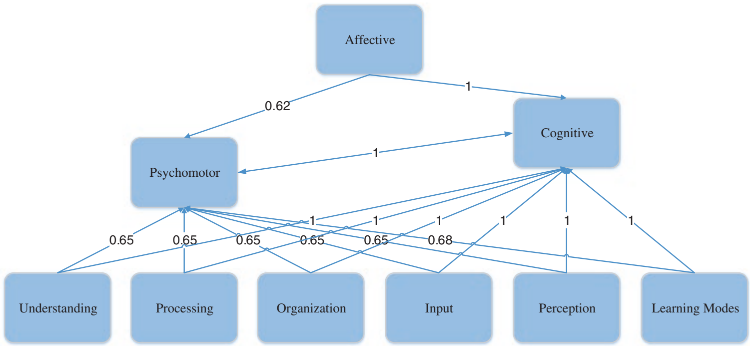

Fig. C.4 The causal relationships between the 9 aspects in the early stage for student S2

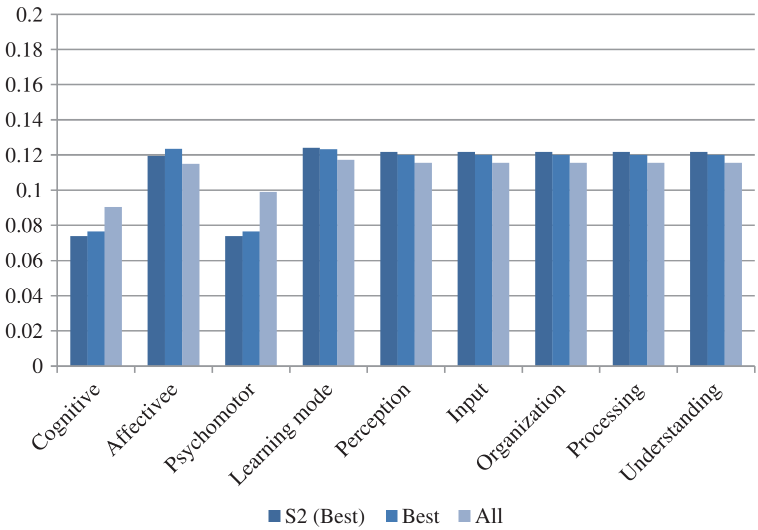

Fig. C.5 Given all subjects, the overall impact distribution of each aspect for student S2 at early stage

effect on each other, i.e., progress in any domain would cause the progress in the other two domains. The balance development of student learning styles would directly affect the performance of cognitive and psychomotor. And the impact of balance degree of learning style on cognitive is larger than that on psychomotor.

At early stage, given all subjects, the overall impact distribution of each aspect for student S2 is shown by Fig. C.5. Besides, the information of best students and all students is provided as references. Because the early stage only measures student basic abilities, so the differences between good students and poor students in the 3 domains are quite small. In this stage, the balance degree of learning styles mainly effects the performance in other aspects. Above all, no matter for different types of students, or for different subjects, the casual relationships between those aspects are quite the same, only the impacts have small differences.

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know a little about my learning situation; 4: know my learning situation; 5: know my learning situation quite well).

C.2 Middle Stage—"Potential of Making Progress"

This part analyzes the potential of making further progress. If a student does not only has good performance in the 3 domains, but also can develop his learning styles balanced according to different teaching modes, then the student has the potential of making progress, and has stronger ability of self-learning. For this type of students, no matter how difficult the learning activities are, or using which way of teaching, they all can have good performance. On the contrary, for the students having "low potential of making progress", teachers should teach them in terms of their learning styles. The evaluation in middle stage also indicates that if the student is making progress in the right direction.

For student S2, the following 3 figures are the analysis results of learning performance in the 9 aspects for all subjects, science subjects, art subjects, respectively. For each figure, the horizontal axis represents different types of students, and student S2, the vertical axis represents their relative performance (0: the worst, 1: the best). The first group of histogram represents student potential, and the second group of histogram represents the balance degree of learning styles. Generally speaking, no matter for which type of subjects, if a student has better overall performance in the 3 domains, then he has better balance degree of learning styles, which means that he has larger potential to make progress. But for different types of subjects of a student, he has different performance in the 3 domains, his balance degrees of learning styles are different, the corresponding potentials also have differences. For example, for all subjects and science subjects, student S2 belongs to best according to his performance in the 3 domains (Figs. C.6 and C.7), however, his performance in art subjects is only good (Fig. C.8).

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know a little about my learning situation; 4: know my learning situation; 5: know my learning situation quite well).

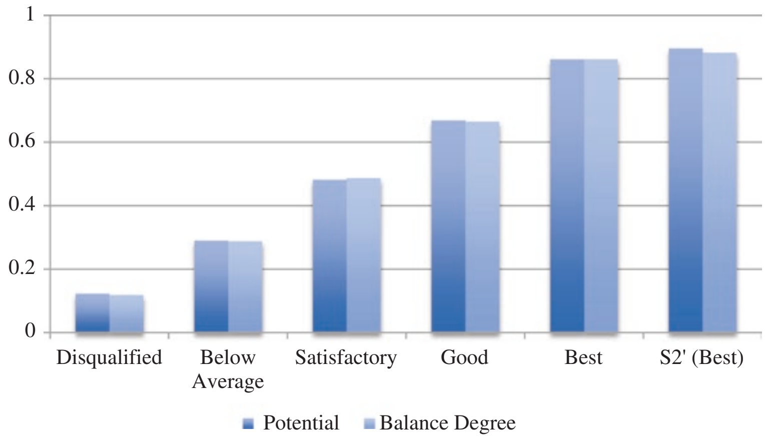

Fig. C.6 All subjects

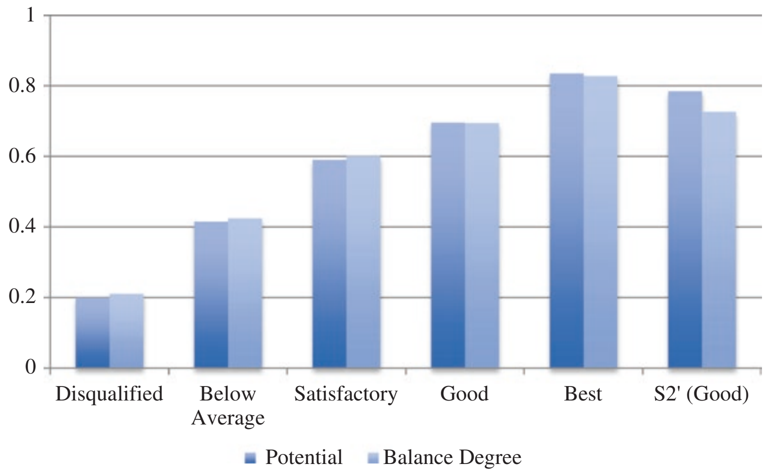

Fig. C.7 Science subjects

C.3 Mature Stage

This stage includes lower levels and higher levels of the 3 domains (cognitive, affective, and psychomotor) to evaluate student, which is especially used to tell the differences between best students and normal students.

Cognitive: cognitive and remember, understand, application, analysis, comprehensive, and creative ability;

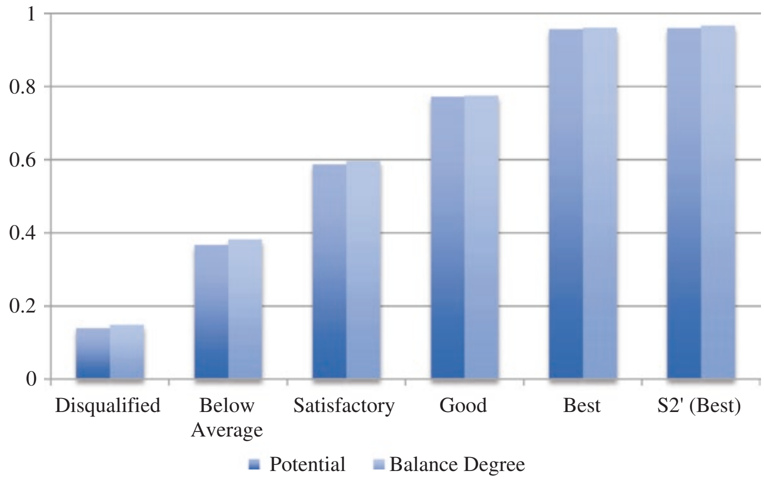

Fig. C.8 Art subjects

Affective: accept knowledge, give response, evaluate, organize, form sense of worth to affect behavior;

Psychomotor: the ability of using sense to guide activities, preparation work before learning, to practice according to guidance, to freely apply knowledge, be good at gained skills, ability of adapting oneself quickly to changing conditions, to solve problems based on creative behavior.

C.3.1 Classification Results

The overall distribution results at mature stage of student S2 are shown by the following figures: (Fig. C.9) all subjects; (Fig. C.10) science subjects; (Fig. C.11) art subjects. The number of students in each group is indicated in the brackets after that type. We can give the same conclusion as "early stage." Those figures show that for all subjects, each type of students has stable performance in different aspects of each domain. The same rule is that if a student has better performance in a domain, then the student would have better performance in other domains. The same conclusion can be applied to science subjects (Fig. C.10) and art subjects (Fig. C.11). However, student S2 (1) has better performance for science subjects than that of art subjects in the 3 domains. For all subjects and science subjects, S2 is best student, but for art subjects, although he can reach the level of best students in the 3 domains, he has to stay at middle level in the highest degree in the domain of affective. So generally speaking, he only has good performance in the 3 domains.

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know

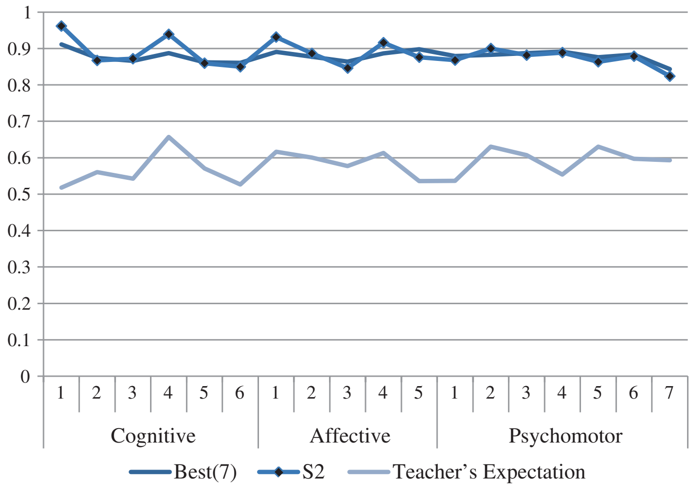

Fig. C.9 All subjects

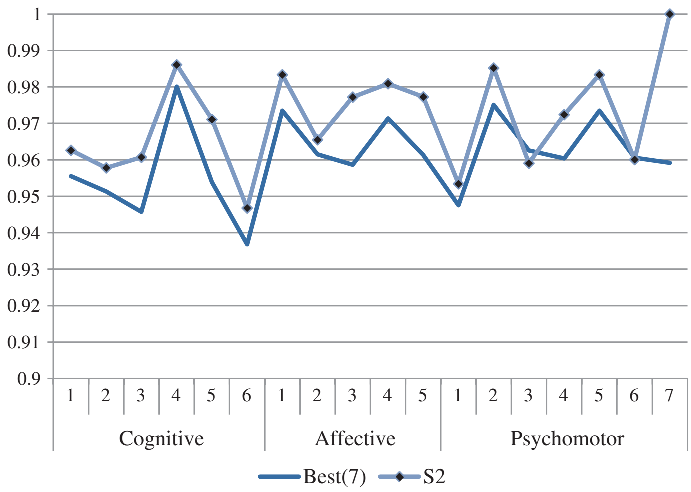

Fig. C.10 Science subjects

a little about my learning situation; 4: know my learning situation; 5: know my learning situation quite well).

C.3.2 Mature Stage—Potential of Making Progress

Similar to the analysis of middle stage, the analysis results are similar to that of early stage, we are not repeat it again here. Generally speaking, S2 still belongs to

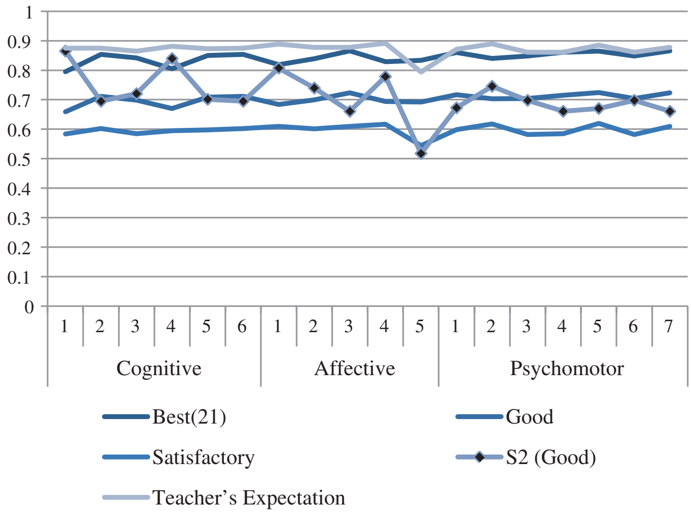

Fig. C.11 Art subjects

best students. The performance of student S2 in all aspect of the 3 domains for all subjects and science subjects is best, only the performance for art subjects is good.

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know a little about my learning situation; 4: know my learning situation; 5: know my learning situation quite well).

C.3.3 The Causal Relationship Between Different Aspects

Similar to the experiment described in section Appendix B.1.2, the changes of an aspect (progress or regress) would affect the changes (progress or regress) of the other aspects, so we have analyzed the casual relationships between the 9 aspects according to the learning performance of student S2. Given all subjects, the causal relationships between the 9 aspects in the early stage for student S2 are shown in Fig. C.12. Psychomotor has become the core aspect, which affect affective and cognitive with each other. In the meantime, because of the learning styles reflecting different characteristics of learning behavior, the changes of any aspects of learning styles can affect the performance in psychomotor.

According to the performance of student S2 for all subjects at mature stage, Fig. C.13 shows the comparison of the overall impact distribution of each aspect on the other aspects for student S2, best student, and all students, respectively. Apparently, at mature stage, student behavior has become the aspect that has the

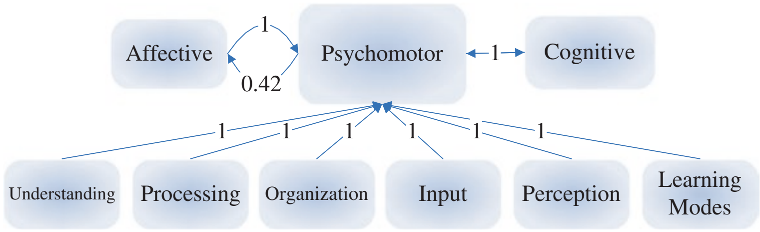

Fig. C.12 The casual relationship between all aspects according to the performance of student S2 for all subjects at mature stage

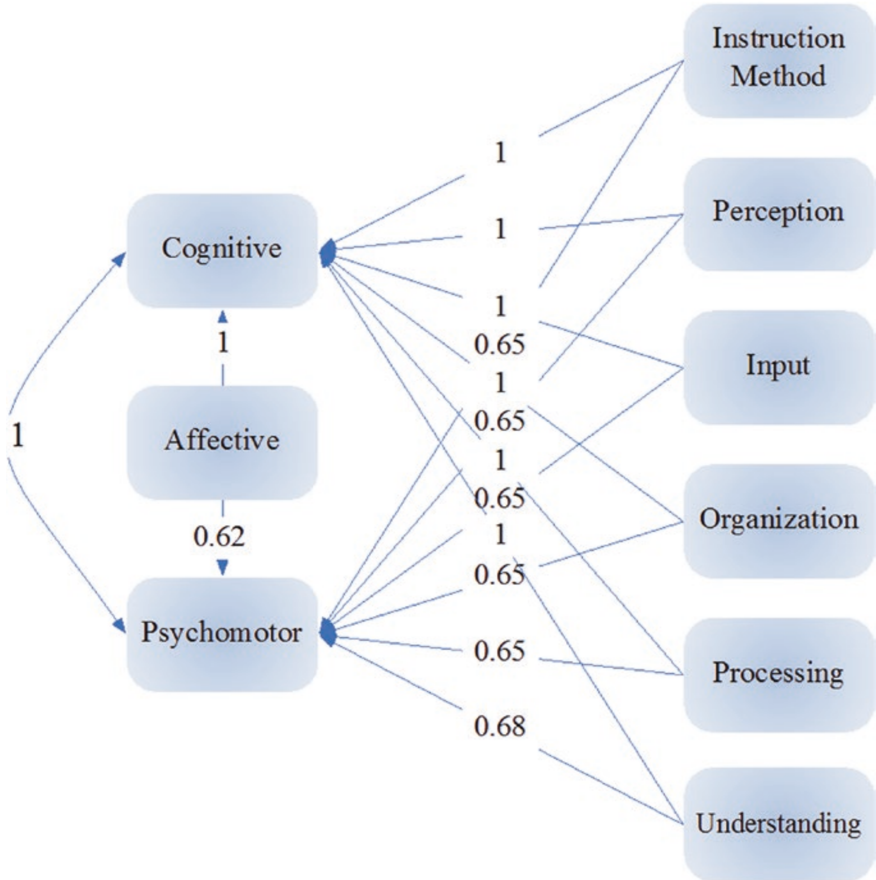

Fig. C.13 The overall impact distribution of each aspect on the other aspects according to the performance of student S2 for all subjects at mature stage largest impact on the other aspects. Above all, no matter for different types of students, or for different subjects, the casual relationships between those aspects are quite the same, and only the impacts have small differences.

If you were student S2, will this analysis results help you better understand your learning situation? (please score from 1 to 5—1: totally do not know my learning situation; 2: not quite sure about my learning situation; 3: only know a little about my learning situation; 4: know my learning situation; and 5: know my learning situation quite well).

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