APPLICATION OF STRUCTURAL EQUATION MODELING
IN EDUCATIONAL RESEARCH AND PRACTICE

CONTEMPORARY APPROACHES TO RESEARCH IN LEARNING INNOVATIONS

Volume 7

Rationale:
Learning today is no longer confined to schools and classrooms. Modern information and communication technologies make the learning possible any where, any time. The emerging and evolving technologies are creating a knowledge era, changing the educational landscape, and facilitating the learning innovations. In recent years educators find ways to cultivate curiosity, nurture creativity and engage the mind of the learners by using innovative approaches.

Contemporary Approaches to Research in Learning Innovations explores approaches to research in learning innovations from the learning sciences view. Learning sciences is an interdisciplinary field that draws on multiple theoretical perspectives and research with the goal of advancing knowledge about how people learn. The field includes cognitive science, educational psychology, anthropology, computer and information science and explore pedagogical, technological, sociological and psychological aspects of human learning. Research in this approaches examine the social, organizational and cultural dynamics of learning environments, construct scientific models of cognitive development, and conduct design-based experiments.
Contemporary Approaches to Research in Learning Innovations covers research in developed and developing countries and scalable projects which will benefit everyday learning and universal education. Recent research includes improving social presence and interaction in collaborative learning, using epistemic games to foster new learning, and pedagogy and praxis of ICT integration in school curricula.

Application of Structural Equation Modeling in Educational Research and Practice

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TABLE OF CONTENTS

Part I – Theoretical Foundations

Chapter 1
Applying Structural Equation Modeling (SEM) in Educational Research: An Introduction 3
Timothy Teo, Liang Ting Tsai and Chih-Chien Yang

Chapter 2
Structural Equation Modeling in Educational Research: A Primer 23
Yo In'nami and Rie Koizumi

Part II – Structural Equation Modeling in Learning Environment Research

Chapter 3
Teachers' Perceptions of the School as a Learning Environment for Practice-based Research: Testing a Model That Describes Relations between Input, Process and Outcome Variables 55
Marjan Vrijnsen-de Corte, Perry den Brok, Theo Bergen and Marcel Kamp

Chapter 4
Development of an English Classroom Environment Inventory and Its Application in China 75
Liyan Liu and Barry J. Fraser

Chapter 5
The Effects of Psychosocial Learning Environment on Students' Attitudes towards Mathematics 91
Ernest Afari

Chapter 6
Investigating Relationships between the Psychosocial Learning Environment, Student Motivation and Self-Regulation 115
Sunitadevi Velayutham, Jill Aldridge and Ernest Afari

Chapter 7
In/Out-of-School Learning Environment and SEM Analyses on Attitude towards School 135
Hasan Şeker

Chapter 8
Development of Generic Capabilities in Teaching and Learning Environments at the Associate Degree Level 169
Wincy W.S. Lee, Doris Y. P. Leung and Kenneth C.H. Lo

Part III – Structural Equation Modeling in Educational Practice

Chapter 9
Latent Variable Modeling in Educational Psychology: Insights from a Motivation and Engagement Research Program 187
Gregory Arief D. Liem and Andrew J. Martin

Chapter 10
Linking Teaching and Learning Environment Variables to Higher Order Thinking Skills: A Structural Equation Modeling Approach 217
John K. Rugutt

Chapter 11
Influencing Group Decisions by Gaining Respect of Group Members in E-Learning and Blended Learning Environments: A Path Model Analysis 241
Binod Sundararajan, Lorn Sheehan, Malavika Sundararajan and Jill Manderson

Chapter 12
Investigating Factorial Invariance of Teacher Climate Factors across School Organizational Levels 257
Christine DiStefano, Diana Mîndrilă and Diane M. Monrad

Part IV – Conclusion

Chapter 13
Structural Equation Modeling Approaches in Educational Research and Practice 279
Myint Swe Khine

Author Biographies 285

PART I

THEORETICAL FOUNDATIONS

TIMOTHY TEO, LIANG TING TSAI AND CHIH-CHIEN YANG

1. APPLYING STRUCTURAL EQUATION MODELING (SEM) IN EDUCATIONAL RESEARCH: AN INTRODUCTION

INTRODUCTION

The use of Structural Equation Modeling (SEM) in research has increased in psychology, sociology, education, and economics since it was first conceived by Wright (1918), a biometrician who was credited with the development of path analysis to analyze genetic theory in biology (Teo & Khine, 2009). In the 1970s, SEM enjoyed a renaissance, particularly in sociology and econometrics (Goldberger & Duncan, 1973). It later spread to other disciplines, such as psychology, political science, and education (Kenny, 1979). The growth and popularity of SEM was generally attributed to the advancement of software development (e.g., LISREL, AMOS, Mplus, Mx) that have increased the accessibility of SEM to substantive researchers who have found this method to be appropriate in addressing a variety of research questions (MacCallum & Austin, 2000). Some examples of these software include LISREL (LInear Structural RELations) by Joreskog and Sorbom (2003), EQS (Equations) (Bentler, 2003), AMOS (Analysis of Moment Structures) by Arbuckle (2006), and Mplus by Muthén and Muthén (1998-2010).

Over the years, the combination of methodological advances and improved interfaces in various SEM software have contributed to the diverse usage of SEM. Hershberger (2003) examined major journals in psychology from 1994 to 2001 and found that over 60% of these journals contained articles using SEM, more than doubled the number of articles published from 1985 to 1994. Although SEM continues to undergo refinement and extension, it is popular among applied researchers. The purpose of this chapter is to provide a non-mathematical introduction to the various facets of structural equation modeling to researchers in education.

What Is Structural Equation Modeling?

Structural Equation Modeling is a statistical approach to testing hypotheses about the relationships among observed and latent variables (Hoyle, 1995). Observed variables also called indicator variables or manifest variables. Latent variables also denoted unobserved variables or factors. Examples of latent variables in education are math ability and intelligence and in psychology are depression and self-

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 3–21.

confidence. The latent variables cannot be measured directly. Researchers must define the latent variable in terms of observed variables to represent it. SEM is also a methodology that takes a confirmatory (i.e. hypothesis-testing) approach to the analysis of a theory relating to some phenomenon. Byrne (2001) compared SEM against other multivariate techniques and listed four unique features of SEM:

(1) SEM takes a confirmatory approach to data analysis by specifying the relationships among variables *a priori*. By comparison, other multivariate techniques are descriptive by nature (e.g. exploratory factor analysis) so that hypothesis testing is rather difficult to do.

(2) SEM provides explicit estimates of error variance parameters. Other multivariate techniques are not capable of either assessing or correcting for measurement error. For example, a regression analysis ignores the potential error in all the independent (explanatory) variables included in a model and this raises the possibility of incorrect conclusions due to misleading regression estimates.

(3) SEM procedures incorporate both unobserved (i.e. latent) and observed variables. Other multivariate techniques are based on observed measurements only.

(4) SEM is capable of modeling multivariate relations, and estimating direct and indirect effects of variables under study.

Types of Models in SEM

Various types of structural equation models are used in research. Raykov and Marcoulides (2006) listed four that are commonly found in the literature.

(1) Path analytic models (PA)
(2) Confirmatory factor analysis models (CFA)
(3) Structural regression models (SR)
(4) Latent change model (LC)

Path analytic (PA) models are conceived in terms of observed variables. Although they focus only on observed variables, they form an important part of the historical development of SEM and employ the same underlying process of model testing and fitting as other SEM models. Confirmatory factor analysis (CFA) models are commonly used to examine patterns of interrelationships among various constructs. Each construct in a model is measured by a set of observed variables. A key feature of CFA models is that no specific directional relationships are assumed between the constructs as they are correlated with each other only. Structural regression (SR) models build on the CFA models by postulating specific explanatory relationship (i.e. latent regressions) among constructs. SR models are often used to test or disconfirm proposed theories involving explanatory relationships among various latent variables. Latent change (LC) models are used to study change over time. For example, LC models are used to focus on patterns of growth, decline, or both in longitudinal data and enable researchers to examine both intra- and inter-individual differences in patterns of change. Figure 1 shows an example of each type of model. In the path diagram, the observed variables are represented as rectangles (or squares) and latent variables are represented as circles (or ellipses).

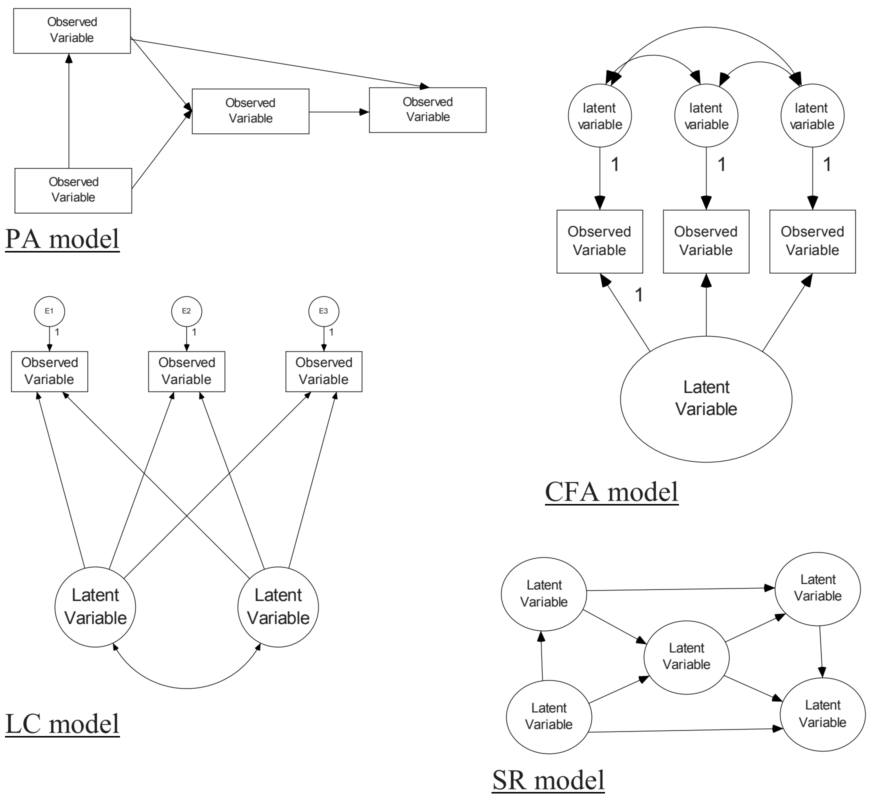


Figure 1. Types of SEM models.

Example Data

Generally, SEM undergoes five steps of model specification, identification, estimation, evaluation, and modifications (possibly). These five steps will be illustrated in the following sections with data obtained as part of a study to examine the attitude towards computer use by pre-service teachers (Teo, 2008, 2010). In this example, we provide a step-by- step overview and non-mathematical using with AMOS of the SEM when the latent and observed variables are continuous. The sample size is 239 and, using the Technology Acceptance Model (Davis, 1989) as the framework data were collected from participants who completed an instrument measuring three constructs: perceived usefulness (PU), perceived ease of use (PEU), and attitude towards computer use (ATCU).

Measurement and Structural Models

Structural equation models comprise both a measurement model and a structural model. The measurement model relates observed responses or 'indicators' to latent variables and sometimes to observed covariates (i.e., the CFA model). The structural model then specifies relations among latent variables and regressions of latent variables on observed variables. The relationship between the measurement and structural models is further defined by the two-step approach to SEM proposed by James, Mulaik and Brett (1982). The two-step approach emphasizes the analysis of the measurement and structural models as two conceptually distinct models. This approach expanded the idea of assessing the fit of the structural equation model among latent variables (structural model) independently of assessing the fit of the observed variables to the latent variables (measurement model). The rationale for the two-step approach is given by Jöreskog and Sörbom (2003) who argued that testing the initially specified theory (structural model) may not be meaningful unless the measurement model holds. This is because if the chosen indicators for a construct do not measure that construct, the specified theory should be modified before the structural relationships are tested. As such, researchers often test the measurement model before the structural model.

A measurement model is a part of a SEM model which specifies the relations between observed variables and latent variables. Confirmatory factor analysis is often used to test the measurement model. In the measurement model, the researcher must operationally decide on the observed indicators to define the latent factors. The extent to which a latent variable is accurately defined depends on how strongly related the observed indicators are. It is apparent that if one indicator is weakly related to other indicators, this will result in a poor definition of the latent variable. In SEM terms, model misspecification in the hypothesized relationships among variables has occurred.

Figure 2 shows a measurement model. In this model, the three latent factors (circles) are each estimated by three observed variables (rectangles). The straight line with an arrow at the end represents a hypothesized effect one variable has on another. The ovals on the left of each rectangle represent the measurement errors (residuals) and these are estimated in SEM.

A practical consideration to note includes avoiding testing models with constructs that contains a single indicator (Bollen, 1989). This is to ensure that the observed indicators are reliable and contain little error so that the latent variables can be better represented. The internal consistency reliability estimates for this example ranged from .84 to .87.

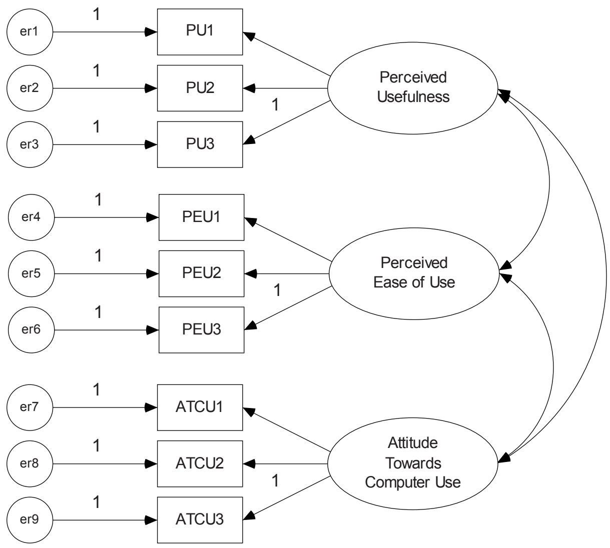


Figure 2. An example of a measurement model.

Structural models differ from measurement models in that the emphasis moves from the relationship between latent constructs and their measured variables to the nature and magnitude of the relationship between constructs (Hair et al., 2006). In other words, it defines relations among the latent variables. In Figure 3, it was hypothesized that a user's attitude towards computer use (ATCU) is a function of perceived usefulness (PU) and perceived ease of use (PEU). Perceived usefulness (PU) is, in turn influenced by the user's perceived ease of use (PEU). Put differently, perceived usefulness mediates the effects of perceived ease of use on attitude towards computer use.

Effects in SEM

In SEM two types of effects are estimates: direct and indirect effects. Direct effects, indicated by a straight arrow, represent the relationship between one latent variable to another and this is indicated using single-directional arrows (e.g. between PU and ATCU in Figure 2). The arrows are used in SEM to indicate directionality and do not imply causality. Indirect effects, on the other hand, reflect the relationship between an independent latent variable (exogenous variable) (e.g. PEU) and a dependent latent variable (endogenous variable) (e.g. ATCU) that is mediate by one or more latent variable (e.g. PU).

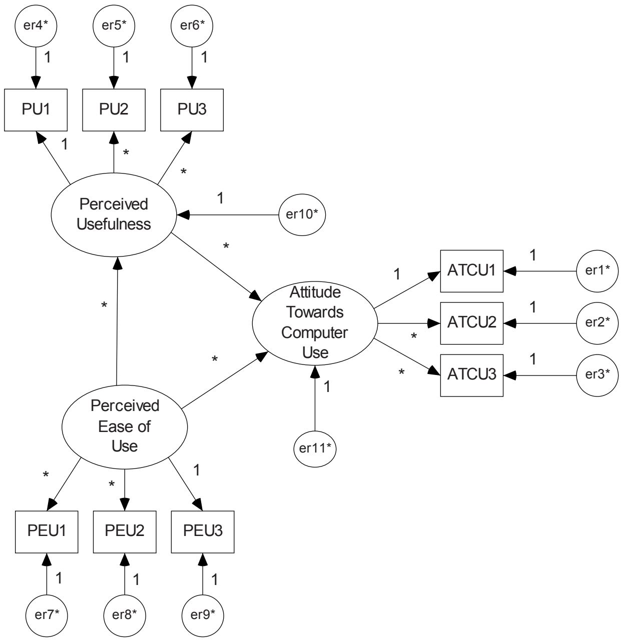


Figure 3. An example of a structural model
Note: An asterisk is where parameter has to be estimated

STAGES IN SEM

From the SEM literature, there appears an agreement among practitioners and theorists that five steps are involved in testing SEM models. These five steps are model specification, identification, estimation, evaluation, and modification (e.g., Hair et al., 2006; Kline, 2005; Schumacker & Lomax, 2004).

Model Specification

At this stage, the model is formally stated. A researcher specifies the hypothesized relationships among the observed and latent variables that exist or do not exist in the model. Actually, it is the process by the analyst declares which relationships are null, which are fixed to a constant, and which are vary. Any relationships among variables that are unspecified are assumed to be zero. In Figure 3, the effect of PEU on ATCU is mediated by PU. If this relationship is not supported, then misspecification may occur.

Relationships among variables are represented by parameters or paths. These relationships can be set to fixed, free or constrained. *Fixed parameters* are not estimated from the data and are typically fixed at zero (indicating no relationship between variables) or one. In this case where a parameter is fixed at zero, no path (straight arrows) is drawn in a SEM diagram. *Free parameters* are estimated from the observed data and are assumed by the researcher to be non-zero (these are shown in Figure 3 by asterisks). *Constrained parameters* are those whose value is specified to be equal to a certain value (e.g. 1.0) or equal to another parameter in the model that needs to be estimated. It is important to decide which parameters are fixed and which are free in a SEM because it determines which parameters will be used to compare the hypothesized diagram with the sample population variance and covariance matrix in testing the fit of the model. The choice of which parameters are free and which are fixed in a model should be guided by the literature.

There are three types of parameters to be specified: directional effects, variances, and covariances. Directional effects represent the relationships between the observed indicators (called factor loadings) and latent variables, and relationships between latent variables and other latent variables (called path coefficients). In Figure 3, the directional arrows from the latent variable, PU to PU2 and PU3 are examples of factor loading to be estimated while the factor loading of PU1 has been set at 1.0. The arrow from PU to ATCU is an example of path coefficient showing the relationship between one latent variable (exogenous variable) to another (endogenous variable). The directional effects in Figure 3 are six factor loadings between latent variables and observed indicators and three path coefficients between latent variables, making a total of nine parameters.

Variances are estimated for independent latent variables whose path loading has been set to 1.0. In Figure 3, variances are estimated for indicator error (er1~er9) associated with the nine observed variables, error associated with the two endogenous variables (PU and ATCU), and the single exogenous variable (PEU). Covariances are nondirectional associations among independent latent variables (curved double-headed arrows) and these exist when a researcher hypothesizes that two factors are correlated. Based on the theoretical background of the model in Figure 3, no covariances were included. In all, 21 parameters (3 path coefficients, 6 factor loadings, and 12 variances) in Figure 3 were specified for estimation.

Model Identification

At this stage, the concern is whether a unique value for each free parameter can be obtained from the observed data. This is dependent on the choice of the model and the specification of fixed, constrained and free parameters. Schumacker and Lomax (2004) indicated that three identification types are possible. If all the parameters are determined with just enough information, then the model is 'just-identified'. If there is more than enough information, with more than one way of estimating a parameter, then the model is 'overidentified'. If one or more parameters may not be determined due to lack of information, the model is 'under-identified'. This situation causes the positive degree of freedom. Models need to be overidentified in order to be estimated and in order to test hypotheses about the relationships among variables. A researcher has to ensure that the elements in the correlation matrix (i.e. the off-diagonal values) that is derived from the observed variables are more than the number of parameters to be estimated. If the difference between the number of elements in the correlation matrix and the number of parameters to be estimated is a positive figure (called the degree of freedom), the model is over-identified. The following formula is used to compute the number of elements in a correlation matrix:

$$[p\,(p+1)]/2$$

where p represents the number of observed(measured) variables. Applying this formula to the model in Figure 3 with nine observed variables, [9(9+1)]/2 = 45. With 21 parameters specified for estimation, the degree of freedom is 45-21= 24, rendering the model in Figure 3 over-identified. When the degree of freedom is zero, the model is just-identified. On the other hand, if there are negative degrees of freedom, the model is under-identified and parameter estimation is not possible. Of the goals in using SEM, an important one is to find the most parsimonious model to represent the interrelationships among variables that accurately reflects the associations observed in the data. Therefore, a large degree of freedom implies a more parsimonious model. Usually, model specification and identification precede data collection. Before proceeding to model estimation, the researcher has to deal with issues relating to sample size and data screening.

Sample size. This is an important issue in SEM but no consensus has been reached among researchers at present, although some suggestions are found in the literature (e.g., Kline, 2005; Ding, Velicer, & Harlow, 1995; Raykov & Widaman, 1995). Raykov and Widaman (1995) listed four requirements in deciding on the sample size: model misspecification, model size, departure from normality, and estimation procedure. Model misspecification refers to the extent to which the hypothesized model suffers from specification error (e.g. omission of relevant variables in the model). Sample size impacts on the ability of the model to be estimated correctly and specification error to be identified. Hence, if there are concerns about specification error, the sample size should be increased over what would otherwise be required. In terms of model size, Raykov and Widaman (1995) recommended that the minimum sample size should be greater than the elements in the correlation matrix, with preferably ten participants per parameter estimated. Generally, as the model complexity increases, so does the larger sample size requirements. If the data exhibit nonnormal characteristics, the ratio of participants to parameters should be increased to 15 in to ensure that the sample size is large enough to minimize the impact of sampling error on the estimation procedure. Because Maximum Likelihood Estimation (MLE) is a common estimation procedure used in SEM software, Ding, Velicer, and Harlow (1995) recommends that the minimum sample size to use MLE appropriately is between 100 to 150 participants. As the sample size increases, the MLE method increases its sensitivity to detect differences among the data.

Kline (2005) suggested that 10 to 20 participants per estimated parameter would result in a sufficient sample. Based on this, a minimum of 10 x 21=210 participants is needed to test the model in Figure 3. The data set associated with Figure 3 contains 239 cases so this is well within the guidelines by Kline. Additionally, Hoelter's critical N is often used as the standard sample size that would make the obtained fit (measured by χ^2) significant at the stated level of significance (Hoelter, 1983). Hoelter's critical N is a useful reference because it is found in most SEM software (e.g., AMOS).

Multicollinearity. This refers to situations where measured variables (indicators) are too highly related. This is a problem in SEM because researchers use related measures as indicators of a construct and, if these measures are too highly related, the results of certain statistical tests may be biased. The usual practice to check for multicollinearity is to compute the bivariate correlations for all measured variables. Any pair of variables with a correlations higher than r = .85 signifies potential problems (Kline, 2005). In such cases, one of the two variables should be excluded from further analysis.

Multivariate normality. The widely used methods in SEM assume that the multivariate distribution is normally distributed. Kline (2005) indicated that all the univariate distributions are normal and the joint distribution of any pair of the variables is bivariate normal. The violation of these assumptions may affect the accuracy of statistical tests in SEM. For example, testing a model with nonnormally distributed data may incorrectly suggest that the model is a good fit to the data or that the model is a poor fit to the data. However, this assumption is hardly met in practice. In applied research, multivariate normality is examined using Mardia's normalized multivariate kurtosis value. This is done by comparing the Mardia's coefficient for the data under study to a value computed based on the formula $p(p+2)$ where p equals the number of observed variables in the model (Raykov & Marcoulides, 2008). If the Mardia's coefficient is lower than the value obtained from the above formula, then the data is deemed as multivariate normal. As with the Hoelter's critical N, the Mardia's coefficient is found most SEM software (e.g., AMOS).

Missing data. The presence of missing is often due to factors beyond the researcher's control. Depending on the extent and pattern, missing data must be addressed if the missing data occur in a non-random pattern and are more than ten percent of the overall data (Hair et al., 2006). Two categories of missing data are described by Kline (2005): missing at random (MAR) and missing completely at random (MCAR). These two categories are ignorable, which means that the pattern of missing data is not systematic. For example, if the absence of the data occurs in X variable and this absence occur by chance and are unrelated to other variables; the data loss is considered to be at random.

A problematic category of missing data is known as not missing at random (NMAR), which implies a systematic loss of data. An example of NMAR is a situation where participants did not provide data on the interest construct because they have few interests and chose to skip those items. Another NMAR case is where data is missing due to attrition in longitudinal research (e.g., attrition due to death in a health study). To deal with MAR and MCAR, users of SEM employ methods such as listwise deletion, pairwise deletion, and multiple imputations. As to which method is most suitable, researchers often note the extent of the missing data and the randomness of its missing. Various comprehensive reviews on missing data such as Allison (2003), Tsai and Yang (2012), and Vriens and Melton (2002) contain details on the categories of missing data and the methods for dealing with missing data should be consulted by researchers who wish to gain a fuller understanding in this area.

Model Estimation

In estimation, the goal is to produce a $\mathbf{\Sigma}(\theta)$ (estimated model-implied covariance matrix) that resembles **S** (estimated sample covariance matrix) of the observed indicators, with the residual matrix ($\mathbf{S} - \mathbf{\Sigma}(\theta)$) being as little as possible. When $\mathbf{S} - \mathbf{\Sigma}(\theta) = \mathbf{0}$, then χ^2 becomes zero, and a perfect model is obtained for the data. Model estimation involves determining the value of the unknown parameters and the error associated with the estimated value. As in regression, both unstandardized and standardized parameter values and coefficients are estimated. The unstandardized coefficient is analogous to a Beta weight in regression and dividing the unstandardized coefficient by the standard error produces a z value, analogous to the t value associated with each Beta weight in regression. The standardized coefficient is analogous to β in regression.

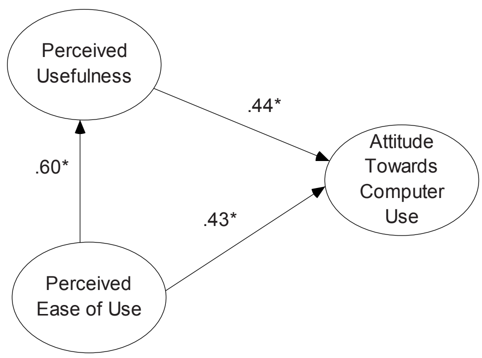
Many software programs are used for SEM estimation, including LISREL (Linear Structural Relationships; Jöreskog & Sörbom, 1996), AMOS (Analysis of Moment Structures; Arbuckle, 2003), SAS (SAS Institute, 2000), EQS (Equations; Bentler, 2003), and Mplus (Muthén & Muthén, 1998-2010). These software programs differ in their ability to compare multiple groups and estimate parameters for continuous, binary, ordinal, or categorical indicators and in the specific fit indices provided as output. In this chapter, AMOS 7.0 was used to estimate the parameters in Figure 3. In the estimation process, a fitting function or estimation procedure is used to obtain estimates of the parameters in θ to minimize the difference between **S** and $\mathbf{\Sigma}(\theta)$. Apart from the Maximum Likelihood Estimation (MLE), other estimation procedures are reported in the literature, including unweighted least squares (ULS), weighted least squares (WLS), generalized least squares (GLS), and asymptotic distribution free (ADF) methods.

In choosing the estimation method to use, one decides whether the data are normally distributed or not. For example, the ULS estimates have no distributional assumptions and are scale dependent. In other words, the scale of all the observed variables should be the same in order for the estimates to be consistent. On the other hand, the ML and GLS methods assume multivariate normality although they are not scale dependent.

When the normality assumption is violated, Yuan and Bentler (1998) recommend the use of an ADF method such as the WLS estimator that does not assume normality. However, the ADF estimator requires very large samples (i.e., n = 500 or more) to generate accurate estimates (Yuan & Bentler, 1998). In contrast, simple models estimated with MLE require a sample size as small as 200 for accurate estimates.

Estimation example. Figure 3 is estimated using the Maximum Likelihood estimator in AMOS 7.0 (Arbuckle, 2006). Figure 4 shows the standardized results for the structural portion of the full model. The structural portion also call structural regression models (Raykov & Marcoulides, 2000). AMOS provides the standardized and unstandardized output, which are similar to the standardized betas and unstandardized B weights in regression analysis. Typically, standardized estimates are shown but the unstandardized portions of the output are examined for significance. For example, Figure 4 shows the significant relationships ($p < .001$ level) among the three latent variables. The significance of the path coefficient from perceived ease of use (PEU) to perceived usefulness (PU) was determined by examining the unstandardized output, which is 0.540 and had a standard error of 0.069.

Although the critical ratio (i.e., z score) is automatically calculated and provided with the output in AMOS and other programs, it is easily determined whether the coefficient is significant (i.e., $z \geq 1.96$ for $p \leq .05$) at a given alpha level by dividing the unstandardized coefficient by the standard error. This statistical test is an approximately normally distributed quantity (z-score) in large samples (Muthén & Muthén, 1998-2010). In this case, 0.540 divided by 0.069 is 7.826, which is greater than the critical z value (at $p = .05$) of 1.96, indicating that the parameter is significant.



* p < .001

Figure 4. Structural model with path coefficients

Model Fit

The main goal of model fitting is to determine how well the data fit the model. Specifically, the researcher wishes to compare the predicted model covariance (from the specified model) with the sample covariance matrix (from the obtained data). On how to determine the statistical significance of a theoretical model, Schumacker and Lomax (2004) suggested three criteria. The first is a non-statistical significance of the chi-square test and. A non-statistically significant chi-square value indicates that sample covariance matrix and the model-implied covariance matrix are similar. Secondly, the statistical significance of each parameter estimates for the paths in the model. These are known as critical values and computed by dividing the unstandardized parameter estimates by their respective standard errors. If the critical values or t values are more than 1.96, they are significant at the .05 level. Thirdly, one should consider the magnitude and direction of the parameter estimates to ensure that they are consistent with the substantive theory. For example, it would be illogical to have a negative parameter between the numbers of hours spent studying and test scores. Although addressing the second and third criteria is straightforward, there are disagreements over what constitutes acceptable values for global fit indices. For this reason, researchers are recommended to report various fit indices in their research (Hoyle, 1995, Martens, 2005). Overall, researchers agree that fit indices fall into three categories: absolute fit (or model fit), model comparison (or comparative fit), and parsimonious fit (Kelloway, 1998; Mueller & Hancock, 2004; Schumacker & Lomax, 2004).

Absolute fit indices measure how well the specified model reproduces the data. They provide an assessment of how well a researcher's theory fits the sample data (Hair et al., 2006). The main absolute fit index is the χ^2 (chi-square) which tests for the extent of misspecification. As such, a significant χ^2 suggests that the model does not fit the sample data. In contrast, a non-significant χ^2 is indicative of a model that fits the data well. In other word, we want the p-value attached to the χ^2 to be non-significant in order to accept the null hypothesis that there is no significant difference between the model-implied and observed variances and covariances. However, the χ^2 has been found to be too sensitive to sample size increases such that the probability level tends to be significant. The χ^2 also tends to be greater when the number of observed variables increases. Consequently, a non-significant p-level is uncommon, although the model may be a close fit to the observed data. For this reason, the χ^2 cannot be used as a sole indicator of model fit in SEM. Three other commonly used absolute fit indices are described below.

The Goodness-of-Fit index (GFI) assesses the relative amount of the observed variances and covariances explained by the model. It is analogous to the R^2 in regression analysis. For a good fit, the recommended value should be GFI > 0.95 (1 being a perfect fit). An adjusted goodness-of-fit index (AGFI) takes into account differing degree of model complexity and adjusts the GFI by a ratio of the degrees of freedom used in a model to the total degrees of freedom. The standardized root mean square residual (SRMR) is an indication of the extent of error resulting from the estimation of the specified model. On the other hand, the amount of error or residual illustrates how accurate the model is hence lower SRMR values (<.05) represents a better model fit. The root mean square error of approximation (RMSEA) corrects the tendency of the χ^2 to reject models with large same size or number of variables. Like SRMR, a lower RMSEA (<.05) value indicates a good fit and it is often reported with a confidence level at 95% level to account for sampling errors associated with the estimated RMSEA.

In comparative fitting, the hypothesized model is assessed on whether it is better than a competing model and the latter is often a baseline model (also known as a null model), one that assumes that all observed variables is uncorrelated. A widely-used index example is the Comparative Fit Index (CFI) which indicates the relative lack of fit of a specified model versus the baseline model. It is normed and varies from 0 to 1, with higher values representing better fit. The CFI is widely used because of its strengths, including its relative insensitivity to model complexity. A value of > .95 for CFI is associated with a good model. Another comparative fit index is the Tucker-Lewis Index (TLI), also called the Bentler-Bonnet NNFI (nonnormed fit index) by Bentler and Bonnet (1980) is used to compare a proposed model to the null model. Since the TLI is not normed, its values can fall below 0 or above 1. Typically, models with a good fit have values that approach 1.0.

Parsimonious indices assess the discrepancy between the observed and implied covariance matrix while taking into account a model's complexity. A simple model with fewer estimated parameters will always get a parsimony fit. This is because although adding additional parameters (thus increasing the complexity of a model) will always improve the fit of a model but it may not improve the fit enough to justify the added complexity. The parsimonious indices are computed using the parsimony ratio (PR), which is calculated as the ratio of degrees of freedom used by the model to the total degrees of freedom available (Marsh, Balla, & McDonald, 1988). An example of parsimony fit indices is the parsimony comparative-of-fit index (PCFI), which adjust the CFI using the PR. The PCFI values of a model range from 0 to 1 and is often used in conjunction with the PCFI of another model (e.g. null model). Because the AGFI and RMSEA adjust for model complexity, they may be also used as indicators of model parsimony.

Test of Model Fit Using Example Model

Most of the above fit indices are used to test the model in Figure 3 and their results shown in Table 1. These model fit indices represent the three fit indices categories absolute fit, comparative fit, and parsimonious fit. It can be seen the fit indices contradict each other. Although the GFI, SRMR, CFI, and the TLI, the significant χ^2, high RMSEA and AGFI suggest that the model may be a poor fit to the data. The fit indices suggests that some misspecification may exist that suggests that the model may not fit well.

Table 1. Model fit for Figure 3

Fit Index	Model in Figure 3	Recommended level	Reference
χ^2	61.135, significant	Non-significant	Hair et al. (2006)
GFI	.94	< .95	Schumacker & Lomax (2004)
AGFI	.89	< .95	Schumacker & Lomax (2004)
SRMR	.04	< .08	Hu & Bentler (1998)
RMSEA	.08	< .07	Hair et al. (2006)
CFI	.97	> .95	Schumacker & Lomax (2004)
TLI	.95	> .95	Schumacker & Lomax (2004)

Note: GFI= Goodness-of-Fit; AGFI=Adjusted Goodness-of-Fit; SRMR=Standardized Root Mean Residual; RMAES= Root Mean Square Error of Approximation; CFI=Comparative Fit Index; TLI=Tucker-Lewis Index

Parameter estimates. Having considered the structural model, it is important to consider the significance of estimated parameters. As with regression, a model that fits the data well but has few significant parameters is not desirable. From the standardized estimates in Figure 4 (the path coefficients for the observed indicators are not shown here because they would have been examined for significance during the confirmatory factor analysis in the measurement model testing stage), it appears that there is a stronger relationship between perceived ease of use (PEU) and perceived usefulness (PU) (β = .60) than between perceived ease of use (PEU) and attitude towards computer use (ATCU) (β = .43). However, the relationship between PEU and ATCU is also mediated by PU, so two paths from PEU and ATCU can be traced in the model (PEU → PU → ATCU). Altogether, PU and PEU explain 60.8% of the variance in ATCU. This is also known as squared multiple correlations and provided in the AMOS output.

Model Modification

If the fit of the model is not good, hypotheses can be adjusted and the model retested. This step is often called re-specification (Schumacker & Lomax, 2004). In modifying the model, a researcher either adds or removes parameters to improve the fit. Additionally, parameters could be changed from fixed to free or from free to fixed. However, these must be done carefully since adjusting a model after initial testing increases the chance of making a Type I error. At all times, any changes made should be supported by theory. To assist researchers in the process of model modification, most SEM software such as AMOS compute the modification indices (MI) for each parameter. Also called the Lagrange Multiplier (LM) Index or the Wald Test, these MI report the change in the χ^2 value when parameters are adjusted. The LM indicates the extent to which addition of free parameters increases model fitness while the Wald Test asks whether deletion of free parameters increases model fitness. The LM and Wald Test follow the logic of forward and backward stepwise regression respectively.

The steps to modify the model include the following:

• Examine the estimates for the regression coefficients and the specified covariances. The ratio of the coefficient to the standard error is equivalent to a *z* test for the significance of the relationship, with a $p < .05$ cutoff of about 1.96. In examining the regression weights and covariances in the model you originally specified, it is likely that one will find several regression weights or covariances that are not statistically significant.

• Adjust the covariances or path coefficients to make the model fit better. This is the usual first step in model fit improvement.

• Re-run the model to see if the fit is adequate. Having made the adjustment, it should be noted that the new model is a subset of the previous one. In SEM terminology, the new model is a *nested* model. In this case, the difference in the χ^2 is a test for whether some important information has been lost, with the degrees of freedom of this χ^2 equal to the number of the adjusted paths. For example, if the original model had a χ^2 of 187.3, and you remove two paths that were not significant. If the new χ^2 has a value of 185.2, with 2 degrees of freedom (not statistically significant difference), then important information has not been lost with this adjustment.

• Refer to the modification indices (MI) provided by most SEM programs if the model fit is still not adequate after steps 1 to 3. The value of a given modification index is the amount that the χ^2 value is expected to decrease if the corresponding parameter is freed. At each step, a parameter is freed that produces the largest improvement in fit and this process continues until an adequate fit is achieved (see Figure 5). Because the SEM software will suggest all changes that will improve model fit, some of these changes may be nonsensical. The researcher must always be guided by theory and avoid making adjustments, no matter how well they may improve model fit. Figure 5 shows an example of a set of modification indices from AMOS 7.0.

Martens (2005) noted that model modifications generally result in a better-fitting model. Hence researchers are cautioned that extensive modifications may results in data-driven models that may not be generalizable across samples (e.g., Chou & Bentler, 1990; Green, Thompson, & Babyak, 1998). This problem is likely to occur when researchers (a) use small samples, (b) do not limit modifications to those that are theoretically acceptable, and (c) severely misspecify the initial model (Green et al., 1998). Great care must be taken to ensure that models are modified within the limitations of the relevant theory. Using Figure 3 as an example, if a Wald test indicated that the researcher should remove the freely estimated parameter from perceived ease of use (PEU) to perceived usefulness (PU), the researcher should not apply that modification, because the suggested relationship between PEU and PU has been empirically tested and well documented. Ideally, model modifications suggested by the Wald or Lagrange Multiplier tests should be tested on a separate sample (i.e. cross-validation). However, given the large samples required and the cost of collecting data for cross-validation, it is common to split an original sample into two halves, one for the original model and the other for validation purposes. If the use of another sample is not possible, extreme caution should be exercised when modifying and interpreting modified models.

Covariances: (Group number 1 – Default model)				
			M.I.	Par Change
er7	<-->	er10	17.060	.064
er9	<-->	er10	4.198	-.033
er6	<-->	er9	4.784	-.038
er5	<-->	er11	5.932	-.032
er5	<-->	er7	5.081	.032
er4	<-->	er11	8.212	.039
er4	<-->	er8	4.532	-.032
er3	<-->	er7	4.154	-.042
er2	<-->	er10	4.056	-.032
er2	<-->	er9	8.821	.049
er1	<-->	er10	5.361	.038

Figure 5. An example of modification indices from AMOS 7.0

CONCLUSION

This chapter attempts to describe what SEM is and illustrate the various steps of SEM by analysing an educational data set. It clearly shows that educational research can take advantage of SEM by considering more complex research questions and to test multivariate models in a single study. Despite the advancement of many new, easy-to-use software programs (e.g., AMOS, Lisrel, Mplus) that have increased the accessibility of this quantitative method, SEM is a complex family of statistical procedures that requires the researcher to make some decisions in order to avoid misuse and misinterpretation. Some of these decisions include answering how many participants to use, how to normalize data, what estimation methods and fit indices to use, and how to evaluate the meaning of those fit indices. The approach to answering these questions is presented sequentially in this chapter. However, using SEM is more than an attempt to apply any set of decision rules. To use SEM well involves the interplay of statistical procedures and theoretical understanding in the chosen discipline. Rather, those interested in using the techniques competently should constantly seek out information on the appropriate application of this technique. Over time, as consensus emerges, best practices are likely to change, thus affecting the way researchers make decisions.

This chapter contributes to the literature by presenting a non-technical, non-mathematical, and step-by-step introduction to SEM with a focus for educational researchers who possess little or no advanced Mathematical skills and knowledge. Because of the use of the variance-covariance matrix algebra in solving the simultaneous equations in SEM, many textbooks and ‘introductory’ SEM articles contained formulas and equations that appear daunting to many educational researchers, many of whom consume SEM-based research reports and review journal articles as part of their professional lives. In addition, this chapter embedded an empirical study using a real educational data set to illustrate aspects of SEM at various junctures aimed to enhance the readers' understanding through practical applications of the technique. In view of the need for continuous learning, several suggestions and resources are listed in this chapter to aid readers in further reading and reference. In summary, while this author acknowledge that similar information may be obtained from textbooks and other sources, the strength of this chapter lies in its brevity and conciseness in introducing readers on the background, features, applications, and potentials of SEM in educational research.

APPENDIX

As with many statistical techniques, present and intending SEM users must engage in continuous learning. For this purpose, many printed and online materials are available. Tapping on the affordances of the internet, researchers have posted useful resources and materials for ready and free access to anyone interested in learning to use SEM. It is impossible to list all the resources that are available on the internet. The following are some websites that this author has found to be useful for reference and educational purposes.

Software (http://core.ecu.edu/psyc/wuenschk/StructuralSoftware.htm)
The site Information on various widely-used computer programs by SEM users. Demo and trails of some of these programs are available at the links to this site.

Books (http://www2.gsu.edu/~mkteer/bookfaq.html)
This is a list of introductory and advanced books on SEM and SEM-related topics.

General information on SEM (http://www.hawaii.edu/sem/sem.html)
This is one example of a person-specific website that contains useful information on SEM. There are hyperlinks in this page to other similar sites.

Journal articles (http://www.upa.pdx.edu/IOA/newsom/semrefs.htm)
A massive list of journal articles, book chapters, and whitepapers for anyone wishing to learn about SEM.

SEMNET (http://www2.gsu.edu/~mkteer/semnet.html)
This is an electronic mail network for researchers who study or apply structural equation modeling methods. SEMNET was founded in February 1993. As of November 1998, SEMNET had more than 1,500 subscribers around the world. The archives and FAQs sections of the SEMNET contain useful information for teaching and learning SEM.

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2. STRUCTURAL EQUATION MODELING IN EDUCATIONAL RESEARCH: A PRIMER

INTRODUCTION

Structural equation modeling (SEM) is a collection of statistical methods for modeling the multivariate relationship between variables. It is also called covariance structure analysis or simultaneous equation modeling and is often considered an integration of regression and factor analysis. As SEM is a flexible and powerful technique for examining various hypothesized relationships, it has been used in numerous fields, including marketing (e.g., Jarvis, MacKenzie, & Podsakoff, 2003; Williams, Edwards, & Vandenberg, 2003), psychology (e.g., Cudeck & du Toit, 2009; Martens, 2005), and education (e.g., Kieffer, 2011; Teo & Khine, 2009; Wang & Holcombe, 2010). For example, educational research has benefited from the use of SEM to examine (a) the factor structure of the learner traits assessed by tests or questionnaires (e.g., Silverman, 2010; Schoonen et al., 2003), (b) the equivalency of models across populations (e.g., Byrne, Baron, & Balev, 1998; In'nami & Koizumi, 2012; Shin, 2005), and (c) the effects of learner variables on proficiency or academic achievement at a single point in time (e.g., Ockey, 2011; Wang & Holcombe, 2010) or across time (e.g., Kieffer, 2011; Marsh & Yeung, 1998; Tong, Lara-Alecio, Irby, Mathes, & Kwok, 2008; Yeo, Fearrington, & Christ, 2011). This chapter provides the basics and the key concepts of SEM, with illustrative examples in educational research. We begin with the advantages of SEM, and follow this with a description of Bollen and Long's (1993) five steps for SEM application. Then, we discuss some of the key issues with regard to SEM. This is followed by a demonstration of various SEM analyses and a description of software programs for conducting SEM. We conclude with a discussion on learning more about SEM. Readers who are unfamiliar with regression and factor analysis are referred to Cohen, Cohen, West, and Aiken (2003), Gorsuch (1983), and Tabachnick and Fidell (2007). SEM is an extension of these techniques, and having a solid understanding of them will aid comprehension of this chapter.

ADVANTAGES OF SEM

SEM is a complex, multivariate technique that is well suited for testing various hypothesized or proposed relationships between variables. Compared with a number of statistical methods used in educational research, SEM excels in four aspects (e.g., Bollen, 1989; Byrne, 2012b). First, SEM adopts a confirmatory,

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 23–51.

hypothesis-testing approach to the data. This requires researchers to build a hypothesis based on previous studies. Although SEM can be used in a model-exploring, data-driven manner, which could often be the case with regression or factor analysis, it is largely a confirmatory method. Second, SEM enables an explicit modeling of measurement error in order to obtain unbiased estimates of the relationships between variables. This allows researchers to remove the measurement error from the correlation/regression estimates. This is conceptually the same as correcting for measurement error (or correcting for attenuation), where measurement error is taken into account for two variables by dividing the correlation by the square root of the product of the reliability estimates of the two instruments ($r_{xy} / \sqrt{[r_{xx} \times r_{yy}]}$). Third, SEM can include both unobserved (i.e., latent) and observed variables. This is in contrast with regression analysis, which can only model observed variables, and with factor analysis, which can only model unobserved variables. Fourth, SEM enables the modeling of complex multivariate relations or indirect effects that are not easily implemented elsewhere. Complex multivariate relations include a model where relationships among only a certain set of variables can be estimated. For example, in a model with variables 1 to 10, it could be that only variables 1 and 2 can be modeled for correlation. Indirect effects refer to the situation in which one variable affects another through a mediating variable.

FIVE STEPS IN AN SEM APPLICATION

The SEM application comprises five steps (Bollen & Long, 1993), although they vary slightly from researcher to researcher. They are (a) model specification, (b) model identification, (c) parameter estimation, (d) model fit, and (e) model respecification. We discuss these steps in order to provide an outline of SEM analysis; further discussion on key issues will be included in the next section.

Model Specification

First, model specification is concerned with formulating a model based on a theory and/or previous studies in the field. Relationships between variables – both latent and observed – need to be made explicit, so that it becomes clear which variables are related to each other, and whether they are independent or dependent variables. Such relationships can often be conceptualized and communicated well through diagrams.

For example, Figure 1 shows a hypothesized model of the relationship between a learner's self-assessment, teacher assessment, and academic achievement in a second language. The figure was drawn using the SEM program Amos (Arbuckle, 1994-2012), and all the results reported in this chapter are analyzed using Amos, unless otherwise stated. Although the data analyzed below are hypothetical, let us suppose that the model was developed on the basis of previous studies. Rectangles represent observed variables (e.g., item/test scores, responses to questionnaire items), and ovals indicate unobserved variables. Unobserved variables are also called factors, latent variables, constructs, or traits. The terms *factor* and *latent variable* are used when the focus is on the underlying mathematics (Royce, 1963), while the terms *construct* and *trait* are used when the concept is of substantive interest. Nevertheless, these four terms are often used interchangeably, and, as such, are used synonymously throughout this chapter. Circles indicate measurement errors or residuals. Measurement errors are hypothesized when a latent variable affects observed variables, or one latent variable affects another latent variable. Observed and latent variables that receive one-way arrows are usually modeled with a measurement error. A one-headed arrow indicates a hypothesized one-way direction, whereas a two-headed arrow indicates a correlation between two variables. The variables that release one-way arrows are independent variables (also called exogenous variables), and those that receive arrows are dependent variables (also called endogenous variables). In Figure 1, self-assessment is hypothesized to comprise three observed variables of questionnaire items measuring self-assessment in English, mathematics, and science. These observed variables are said to *load on* the latent variable of self-assessment. Teacher assessment is measured in a similar manner using the three questionnaire items, but this time presented to a teacher. The measurement of academic achievement includes written assignments in English, mathematics, and science. All observed variables are measured using a 9-point scale, and the data were collected from 450 participants. The nine observed variables and one latent variable contained measurement errors. Self-assessment and teacher assessment were modeled to affect academic achievement, as indicated by a one-way arrow. They were also modeled to be correlated with each other, as indicated by a two-way arrow.

Additionally, SEM models often comprise two subsets of models: a measurement model and a structured model. A measurement model relates observed variables to latent variables, or, defined more broadly, it specifies how the theory in question is operationalized as latent variables along with observed variables. A structured model relates constructs to one another and represents the theory specifying how these constructs are related to one another. In Figure 1, the three latent factors – self-assessment, teacher assessment, and academic achievement – are measurement models; the hypothesized relationship between them is a structural model. In other words, structural models can be considered to comprise several measurement models. Since we can appropriately interpret relationships among latent variables only when each latent variable is well measured by observed variables, an examination of the model fit (see below for details) is often conducted on a measurement model before one constructs a structural model.

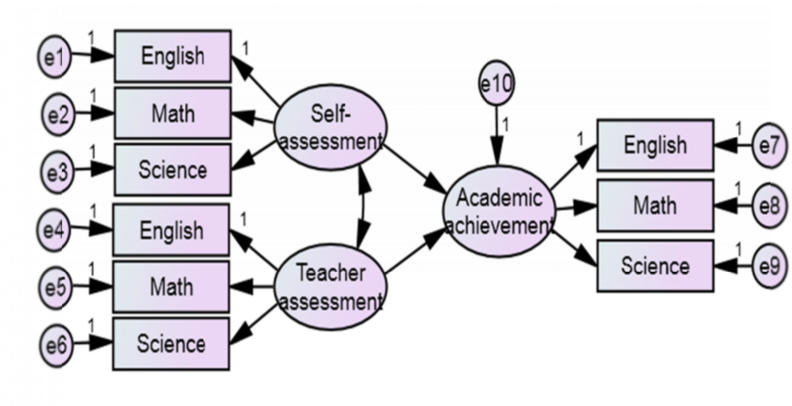

Figure 1. Example SEM model diagram.

Model Identification

The second step in an SEM application, namely model identification, is concerned with whether one can derive a unique value for each parameter (in the model) whose value is unknown (e.g., factor loadings, factor correlations, measurement errors) using the variance/covariance matrix (or the correlation matrix and standard deviations) of the measured variables that *are* known. Models are not identified when there are more parameters than can be estimated from the information available in the variance/covariance matrix. Models that are complex, even if theoretically sound, are likely to have identification problems, particularly when there are a large number of parameters to be estimated relative to the number of variances and covariances in the matrix. Two important principles are applicable to the identification of SEM models. First, latent variables must be assigned a scale (metric) because they are unobserved and do not have predetermined scales. This can be achieved by fixing either a factor variance, or one of the factor loadings, to be a specific value, usually 1. Second, the number of data points in the variance/covariance matrix – known information – must be at least equal to the number of parameters to be estimated in the model (i.e., free parameters) – unknown information. For example, for the academic achievement model, there are 21 estimated parameters: 8 factor loadings, 10 measurement error variances, 1 covariance, and 2 factor variances. Three of the factor loadings are each fixed to be 1 and do not have to be estimated. The number of data points is $p(p + 1)/2$, where p refers to the number of observed variables. For the academic achievement factor in Figure 1, there are nine observed variables, and therefore $9(9 + 1)/2 = 45$ data points. This is larger than the number of parameters to be estimated in the model, which is 21. Thus, this model is identifiable. The degrees of freedom (*df*) are the difference between the number of data points and the number of parameters to be estimated. In the current example, the *df* are 24. When *df* are positive (one or above), models can be identified. When *df* are negative, models cannot be identified, and are called unidentified. When *df* are zero, models can be identified but cannot be evaluated using fit indices (for fit indices, see below).

Parameter Estimation

Third, once the model has been identified, the next step is to estimate parameters in the model. The goal of parameter estimation is to estimate population parameters by minimizing the difference between the observed (sample) variance/covariance matrix and the model-implied (model-predicted) variance/covariance matrix. Several estimation methods are available, including maximum likelihood, robust maximum likelihood, generalized least squares, unweighted least squares, elliptical distribution theory, and asymptotically distribution-free methods. Although the choice of method depends on many factors, such as data normality, sample size, and the number of categories in an observed variable, the most widely used method is maximum likelihood. This is the default in many SEM programs because it is robust under a variety of conditions and is likely to produce parameter estimates that are unbiased, consistent, and efficient (e.g., Bollen, 1989). Maximum likelihood estimation is an iterative technique, which means that an initially posited value is subsequently updated through calculation. The iteration continues until the best values are attained. When this occurs, the model is said to have converged. For the current example in Figure 1, the data were analyzed using maximum likelihood. The subsequent section entitled Data Normality provides more discussion on some recommendations for choice of estimation method.

Model Fit

Fourth, when parameters in a model are estimated, the degree to which the model fits the data must be examined. As noted in the preceding paragraph, the primary goal of SEM analysis is to estimate population parameters by minimizing the difference between the observed and the model-implied variance/covariance matrices. The smaller the difference is, the better the model. This is evaluated using various types of fit indices. A statistically nonsignificant chi-square (χ^2) value is used to indicate a good fit. Statistical nonsignificance is desirable because it indicates that the difference between the observed and the model-implied variance/covariance matrices is statistically nonsignificant, which implies that the two matrices cannot be said to be statistically different. Stated otherwise, a nonsignificant difference suggests that the proposed model cannot be rejected and can be considered correct. Note that this logic is opposite to testing statistical significance for analysis of variance, for example, where statistical significance is usually favorable.

Nevertheless, chi-square tests are limited in that, with large samples, they are likely to detect practically meaningless, trivial differences as statistically significant (e.g., Kline, 2011; Ullman, 2007). In order to overcome this problem, many other fit indices have been created, and researchers seldom depend entirely on chi-square tests to determine whether to accept or reject the model. Fit indices are divided into four types based on Byrne (2006) and Kline (2011), although this classification varies slightly between researchers. First, incremental or comparative fit indices compare the improvement of the model to the null model. The null model assumes no covariances among the observed variables. Fit indices in this category include the comparative fit index (CFI), the normal fit index (NFI), and the Tucker-Lewis index (TLI), also known as the non-normed fit index (NNFI). Second, unlike incremental fit indices, absolute fit indices evaluate the fit of the proposed model without comparing it against the null model. Instead, they evaluate model fit by calculating the proportion of variance explained by the model in the sample variance/covariance matrix. Absolute fit indices include the goodness-of-fit index (GFI) and the adjusted GFI (AGFI). Third, residual fit indices concern the average difference between the observed and the model-implied variance/covariance matrices. Examples are the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA). Fourth, predictive fit indices examine the likelihood of the model to fit in similarly sized samples from the same population. Examples include the Akaike information criterion (AIC), the consistent Akaike information criterion (CAIC), and the expected cross-validation index (ECVI).

The question of which fit indices should be reported has been discussed extensively in SEM literature. We recommend Kline (2011, pp. 209-210) and studies such as Hu and Bentler (1998, 1999) and Bandalos and Finney (2010), as they all summarize the literature remarkably well and clearly present how to evaluate model fit. Kline recommends reporting (a) the chi-square statistic with its degrees of freedom and *p* value, (b) the matrix of correlation residuals, and (c) approximate fit indices (i.e., RMSEA, GFI, CFI) with the *p* value for the close-fit hypothesis for RMSEA. The close-fit hypothesis for RMSEA tests the hypothesis that the obtained RMSEA value is equal to or less than .05. This hypothesis is similar to the use of the chi-square statistic as an indicator of model fit and failure to reject it is favorable and supports the proposed model. Additionally, Hu and Bentler (1998, 1999), Bandalos and Finney (2010), and numerous others recommend reporting SRMR, since it shows the average difference between the observed and the model-implied variance/covariance matrices. There are at least three reasons for this. First, this average difference is easy to understand by readers who are familiar with correlations but less familiar with fit indices. Hu and Bentler (1995) emphasize this, stating that the minimum difference between the observed and the model-implied variance/covariance matrices clearly signals that the proposed model accounts for the variances/covariances very well. Second, a reason for valuing the SRMR that is probably more fundamental is that it is a precise representation of the objective of SEM, which is to reproduce, as closely as possible, the model-implied variance/covariance matrix using the observed variance/covariance matrix. Third, calculation of the SRMR does not require chi-squares. Since chi-squares are dependent on sample size, this indicates that the SRMR, which is not based on chi-squares, is not affected by sample size. This is in contrast with other fit indices (e.g., CFI, GFI, RMSEA), which use chi-squares as part of the calculation. For the assessment and academic achievement data, the chi-square is 323.957 with 24 degrees of freedom at the probability level of .464 ($p > .05$). The matrix of correlation residuals is presented in Table 1. If the model is correct, the differences between sample covariances and implied covariances should be small. Specifically, Kline argues that differences exceeding |0.10| indicate that the model fails to explain the correlation between variables. However, no such cases are found in the current data. Each residual correlation can be divided by its standard error, as presented in Table 2. This is the same as a statistical significance test for each correlation. The well-fitting model should have values of less than |2|. All cases are statistically nonsignificant. The RMSEA, GFI, and CFI are 0.000 (90% confidence interval: 0.000, 0.038), .989, and 1.000, respectively. The p value for the close-fit hypothesis for RMSEA is .995, and the close-fit hypothesis is not rejected. The SRMR is .025. Taken together, it may be reasonable to state that the proposed model of the relationship between self-assessment, teacher assessment, and academic achievement is supported.

The estimated model is presented in Figure 2. The parameter estimates presented here are all standardized as this facilitates the interpretation of parameters. Unstandardized parameter estimates also appear in an SEM output and these should be reported as in Table 3 because they are used to judge statistical significance of parameters along with standard errors. Factor loadings from the factors to the observed variables are high overall (β = .505 to .815), thereby suggesting that the three measurement models of self-assessment, teacher assessment, and academic achievement were each measured well in the current data. A squared factor loading shows the proportion of variance in the observed variable that is explained by the factor. For example, the squared factor loading of English for self-assessment indicates that self-assessment explains 53% of the variance in English for self-assessment (.731 × .731). The remaining 47% of the variance is explained by the measurement error (.682 × .682). In other words, the variance in the observed variable is explained by the underlying factor and the measurement error. Finally, the paths from the self-assessment and teacher assessment factors to the academic achievement factor indicate that they moderately affect academic achievement (β = .454 and .358). The correlation between self-assessment and teacher assessment is rather small (–.101), thereby indicating almost no relationship between them.

Table 1. Correlation residuals

		Self-assessment			Teacher assessment			Academic achievement		
		English	Mathematics	Science	English	Mathematics	Science	English	Mathematics	Science
Self-assessment	English	–								
	Math	0.008	–							
	Science	–0.026	0.005	–						
Teacher	English	0.032	–0.003	–0.023	–					
assessment	Math	0.002	0.015	0.036	0.003	–				
	Science	–0.013	–0.065	–0.014	–0.006	–0.001	–			
Academic	English	0.002	–0.064	0.046	0.048	0.008	–0.023	–		
achievement	Math	0.012	–0.016	0.047	–0.011	0.003	–0.032	0.007	–	
	Science	0.081	0.010	0.029	–0.083	–0.009	0.058	0.000	–0.012	–

Table 2. Standardized correlation residuals

		Self-assessment			Teacher assessment			Academic achievement		
		English	Mathematics	Science	English	Mathematics	Science	English	Mathematics	Science
Self-assessment	English	–								
	Mathematics	0.102	–							
	Science	–0.380	0.092	–						
Teacher assessment	English	0.389	–0.045	–0.358	–					
	Mathematics	0.030	0.314	0.757	0.043	–				
	Science	–0.219	–1.297	–0.284	–0.085	–0.014	–			
Academic achievement	English	0.029	–0.959	0.710	0.567	0.135	–0.371	–		
	Mathematics	0.211	–0.349	1.037	–0.186	0.062	–0.718	0.106	–	
	Science	1.340	0.195	0.608	–1.304	–0.184	1.224	–0.005	–0.261	–

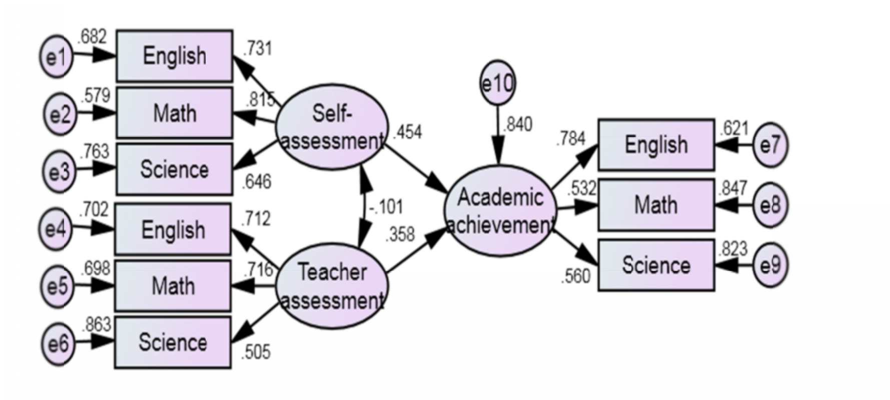

Figure 2. Example of an SEM model with standardized estimates

Model Respecification

Fifth, model re-specification is concerned with improving the model-data fit, for example, by deleting statistically nonsignificant paths or adding paths to the model. Any decision must be theoretically defensible and should not be statistically driven. The results are no longer confirmatory and should be viewed as explanatory. For the assessment and academic achievement data, we could, for example, delete the correlation between self-assessment and teacher assessment as it is very small in size ($r = -.101$) and statistically nonsignificant. This could be done only if it were supported by previous studies. Since this is not the case, no change is made in the model.

Table 3. Unstandardized and standardized estimates

Parameter		B	Standard error	β
Self-assessment –>	English	1.000[a]	–	.731
	Mathematics	.910*	.073	.815
	Science	.703*	.060	.646
Teacher assessment –>	English	1.000[a]	–	.712
	Mathematics	.736*	.086	.716
	Science	.528*	.066	.505
Academic achievement –>	English	1.000[a]	–	.784
	Mathematics	.483*	.060	.532
	Science	.534*	.065	.560
Self-assessment –>	Academic achievement	.498*	.072	.454
Teacher assessment –>	Academic achievement	.380*	.073	.358
Self-assessment <–>	Teacher assessment	–0.092	.058	-.101

Note. [a]*Fixed to 1.000 for scale identification.* **$p < .05$. B refers to unstandardized estimates. β refers to standardized estimates.*

SOME KEY ISSUES

Thus far, we have discussed an SEM analysis with minimal details. In practice, there are several other issues that must be considered in order to use SEM appropriately. We will discuss these issues surrounding data screening, model fit indices, and sample size because of their prevalence in SEM.

Data Screening

Before being put to appropriate use, SEM must undergo data screening. Such preliminary analysis may initially seem tedious; however, if it is done properly, it often saves time and leads to a more precise understanding of the results. Data screening is often discussed in terms of linearity, data normality, outliers, and missing data. Researchers examine these issues in slightly different ways. Readers are referred to Byrne (2006, 2010), Kline (2011), and Tabachnick and Fidell (2007) for further details.

Linearity. SEM models are estimated by examining the relationship – usually a linear one – among measured variables that are represented in the variance/covariance matrix (or the correlation matrix and standard deviations). Such a linear relationship between variables is called linearity: One variable increase/decreases in proportion to a change in another variable. Figure 3A shows an example of this relationship. As with regression and factor analysis, excessive linearity is problematic. This can be examined through inspection of scatterplots or correlation matrices. For example, high correlations among variables (e.g., +/–.90; Tabachnick & Fidell, 2007) – also called multicollinearity – are troublesome. Table 4 shows that the correlations between the observed variables range from –.103 to .601. They are not high enough to cause a problem. Statistical tests for multicollinearity are also available, which include squared multiple correlations, tolerance, and the variance inflation factor. These tests are also used in statistical analysis in general and are not limited to SEM. High linearity can be adjusted for by deleting or aggregating redundant variables.

Nonlinear relationships can also be examined in quadratic or cubic models. A quadratic relationship is one in which one variable affects another up to some point, after which the effect levels off or decreases. Figure 3B shows a data distribution that looks like an inverse U-shape, where as one variable increases (1, 2, 3, 4, 5, 6, 7, 8) the other increases and then decreases (2, 3, 4, 5, 4, 3, 2, 1). A cubic relationship is similar to a quadratic relationship—one variable affects another up to some point, the effect levels off or decreases beyond that point, but this time comes back to influence once again after a certain point. Figure 3C shows a cubic relationship. Quadratic and cubic relationships are also called curvilinear relationships. Figure 3D shows an interactive relationship, in which scores in one group increase while those in the other group decrease. It is possible that a moderator variable is at play. It should be noted that there are a variety of nonlinear relationships in addition to those presented in Figures 3B, 3C, and 3D (e.g., U-shaped relationship for a quadratic one). As a standard SEM assumes linear relations, modeling a nonlinear effect requires advanced techniques (see Kline, 2005, 2011; Marsh, Wen, Nagengast, & Hau, 2012).

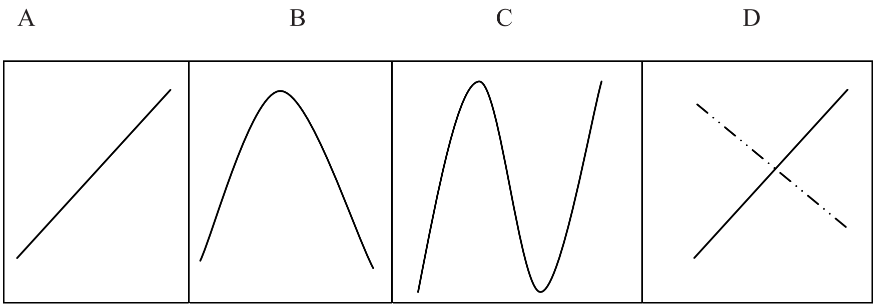

Figure 3. Linear, quadratic, cubic, and interactive relationships

Data normality. Data normality is divided into univariate normality and multivariate normality. Univariate normality refers to the situation in which one variable is normally distributed. Multivariate normality refers to the situation in which, in addition to the normality of each variable, each variable is also normally distributed for each other variable (Tabachnick & Fidell, 2007). Numerous SEM application studies use the maximum likelihood estimation method. This method assumes multivariate normal distribution of the data for the dependent (i.e., endogenous) variable. Although maximum likelihood methods are robust against non-normality, it is still important to assess whether the data satisfy the assumption of normality. Since multivariate normality is related to univariate normality, both types of normality need to be examined.

Univariate normality can be examined by inspecting absolute skewness and kurtosis values or the statistical significance of those values. First, with regard to the inspection of skewness and kurtosis, data normality is ensured when both values are zero. Unfortunately, there are no clear-cut guidelines on the degree of non-normality. Kline (2011) reviewed relevant studies (e.g., Curran, West, & Finch, 1996) and suggested viewing skewness and kurtosis exceeding 3 and 20 respectively as extremely non-normal. Note that this is a rule-of-thumb and is not an agreed-upon definition. For example, Curran et al. (1996) consider a skewness of 2 and a kurtosis of 7 as moderately non-normal, and a skewness of 3 and a kurtosis of 21 as severely non-normal. Chou and Bentler (1995) and Muthén and Kaplan (1985) argue that skewness and kurtosis values approaching 2 and 7, respectively, indicate problems. Table 4 shows that skewness and kurtosis values for all the observed variables are well below these cut-offs and are in fact very near to zero, thereby indicating that the data are univariately normal.

Table 4. Correlations between variables and their descriptive statistics

		Self-assessment			Teacher assessment			Academic achievement		
		English	Mathematics	Science	English	Mathematics	Science	English	Mathematics	Science
Self-assessment	English	–								
	Mathematics	.601	–							
	Science	.452	.531	–						
Teacher assessment	English	–.034	–.061	–.063	–					
	Mathematics	–.052	–.044	–.011	.513	–				
	Science	–.048	–.103	–.046	.356	.361	–			
Academic achievement	English	.241	.220	.246	.202	.182	.106	–		
	Mathematics	.172	.164	.193	.109	.122	.050	.423	–	
	Science	.235	.200	.180	.063	.117	.146	.439	.285	–
Mean		4.089	4.102	4.088	4.077	4.158	4.078	4.177	4.072	4.063
SD		1.284	1.048	1.021	1.361	0.996	1.013	1.313	0.935	0.981
Minimum		0.412	1.099	1.281	0.040	1.724	1.061	0.468	1.601	1.171
Maximum		8.423	6.984	6.776	8.625	7.549	7.383	7.712	7.230	6.736
Skewness		0.095	0.035	0.016	–0.065	0.148	–0.035	–0.119	0.128	–0.072
z		0.819	0.299	0.137	–0.565	1.273	–0.298	–1.031	1.106	–0.623
Kurtosis		0.135	0.006	–0.326	–0.360	0.208	0.164	–0.166	–0.218	–0.013
z		0.520	–0.031	–1.453	–1.599	0.831	0.644	–0.768	–0.992	–0.112

Second, the statistical significance of skewness and kurtosis also serves as an indicator of data normality. In particular, the critical ratio or z value is computed by dividing either skewness or kurtosis by its standard error. Data normality is ensured when the absolute value is within +/– 2.58 ($p < .01$) or 3.29 ($p < .001$). However, as emphasized by Kline (2011) and Tabachnick and Fidell (2007), the standard errors of skewness and kurtosis shrink in large sample sizes, which can produce statistically significant skewness and kurtosis values even when the data distribution appears normal. Thus, with large samples, making substantive decisions on the basis of the visual inspection of the data – for example, using histograms or box plots – is preferred. However, it is difficult to define what is meant by a large sample. For example, Byrne (2006, 2010) only uses absolute skewness and kurtosis values for her dataset with a sample size of 372. Ullman (2007) uses both absolute values and statistical significance of skewness and kurtosis for her two datasets with sample sizes 175 and 459. In actuality, it appears that researchers are more likely to use estimation methods that are robust against non-normality, such as Satorra-Bentler correction or weighted least square parameter estimate methods. In any case, Table 4 shows that z values for skewness and kurtosis are all within +/–2.58 ($p < .01$) or 3.29 ($p < .001$), thereby suggesting data normality.

Additionally, multivariate normality can be measured using Mardia's coefficient of multivariate kurtosis. The statistical significance of Mardia's coefficient is examined using a z value, but this time using the z values of 5 or 6, not +/–2.58 ($p < .01$) or 3.29 ($p < .001$), since Bentler (2005) argues that multivariate non-normality would not affect the model in practice unless its values were 5, 6, or above. Univariate normality can be estimated using general-purpose software programs (e.g., SAS or SPSS) or SEM programs, whereas multivariate normality can only be estimated using SEM programs (for SEM programs, see the Software section). Mardia's coefficient for the current data is –.157 with a z value of –.119. This indicates the multivariate normality of the data.

As seen above, numerous issues surrounding the treatment of non-normal data complicate decision making during data analysis. We reviewed previous studies and found Finney and DiStefano (2006) the most accessible, synthetic, and up to date. They summarize relevant studies and recommend that, for continuous data, if the variables are approximately normally distributed, the maximum likelihood estimation is recommended; if the variables are moderately non-normal (skewness < 2 and kurtosis < 7) the maximum likelihood estimation or Satorra-Bentler correction method are recommended; if the variables are severely non-normal (skewness > 2 and kurtosis > 7), the Satorra-Bentler correction or bootstrapping methods is recommended. For categorical data, regardless of the number of categories, they recommend using weighted least square parameter estimates (WLSMV), available in the SEM program Mplus. If Mplus is not available, they recommend that if the variables are approximately normally distributed, the maximum likelihood estimation should be used for scales with five or more categories and the Satorra-Bentler correction method for scales with four or more categories. This also applies to moderately non-normal data (skewness < 2 and kurtosis < 7). If the variables are severely non-normal (skewness > 2 and kurtosis > 7), the Satorra-Bentler correction method is recommended.

Outliers. An outlier is an extremely large or small value of one variable (a univariate outlier) or a combination of such values of two or more variables (a multivariate outlier). Univariate outliers can be detected by drawing a histogram or inspecting the z values of variables using, for example, the SPSS EXPLORE or DESCRIPTIVES functions. Multivariate outliers can be detected using the Mahalanobis distance (i.e., Mahalanobis d-squared) statistic. It shows how one observation in the data is distantly located from the others. It is distributed as a chi-square statistic with degrees of freedom equal to the number of observed variables. Observations are arranged according to the size of the statistics, and those exceeding the critical value of the chi-square given degrees of freedom (e.g., $p < .001$) can be judged as outliers. For the current data, the histograms appear normal. There are five responses out of 4050 (450 × 9 items) exceeding the z value 3.29 ($p < .001$). As this is just 0.001% of the total responses, it is considered negligible. With regard to multivariate outliers, the critical value of chi-square for 24 degrees of freedom is 51.179. The most deviated case was participant 4, whose responses produced a Mahalanobis distance of 27.192—still below 51.179. Taken together, it is reasonable to say that the current dataset does not include univariate or multivariate outliers.

Missing data. The ideal situation is to be able to analyze a complete dataset that contains all examinees' responses to all items. In reality, this rarely occurs and one often has to analyze a dataset with missing values. Therefore, how to treat missing data is a widely discussed issue in the application of statistics, including SEM. Missing data treatment is classified into three types: (a) the deletion of those data, (b) the estimation of those data, and (c) the use of parameter estimation methods that take missingness into consideration. Deletion of missing data is a traditional approach, and includes listwise deletion (elimination of all cases with missing values from subsequent analysis) or pairwise deletion (removal of paired cases in which at least one case has a missing value). Although both methods are easy to implement, they may result in substantial loss of data observations. More importantly, Muthén, Kaplan, and Hollis (1987) argue that the two methods work only when data are missing completely at random, a case that is often violated in practice. Thus, both listwise and pairwise deletion methods may bias results if data missingness is not randomly distributed through the data (Tabachnick & Fidell, 2007).

A preferred approach is to estimate and impute missing data. Methods abound, such as mean substitution, regression, and expectation maximization methods; however, according to Tabachnick and Fidell (2007), the most recommended method is multiple imputation (Rubin, 1987). It replaces missing values with plausible values that take into account random variation.

Another way to address missing data is to use parameter estimation methods that take missingness into consideration. This is implemented in (full information) maximum likelihood estimation, which uses all available data regardless of completeness (e.g., Enders, 2001). Both expectation maximization and maximum likelihood estimation methods are available in SEM programs. As the current data do not include missing responses, it is not necessary to eliminate, estimate, or impute such responses.

Model Fit Indices

Although no agreed-upon guidelines exist regarding which fit indices should be reported, some recommendations can be found in the literature. In an often-cited article, Hu and Bentler (1998, 1999) recommend reporting (a) the SRMR, and (b) the CFI, TLI, RMSEA, or other indices (e.g., Gamma Hat, Incremental Fit Index [IFI], McDonald's Centrality Index [MCI], Relative Noncentrality Index [RNI]). Similarly, Kashy, Donnellan, Ackerman, and Russell (2009) recommend reporting the CFI or TLI along with the chi-square and RMSEA. Bandalos and Finney (2010) recommend the chi-square, CFI, TLI, RMSEA, and SRMR, whereas Mueller and Hancock (2010) recommend RMSEA and its confidence interval, the SRMR, and at least one of CFI, NFI, and TLI. Widaman (2010) encourages reporting the chi-square, CFI, TLI, and RMSEA. For testing measurement invariance across groups (e.g., whether the factor loadings are the same across groups), Cheung and Rensvold (2002) recommend reporting the CFI, Gamma Hat, and McDonald's Noncentrality Index and interpreting a reduction in each index as evidence of measurement invariance. Summarizing studies that provide guidelines for reporting fit indices, In'nami and Koizumi (2011) report that the indices recommended most often are the chi-square (with degrees of freedom and p values), CFI, TLI, RMSEA (and its confidence interval), and the SRMR.

Sample Size

One rule-of-thumb is that a sample size below 100, between 100 and 200, and over 200 is often considered small, medium, and large, respectively (Kline, 2005). Similarly, Ding, Velicer, and Harlow (1995) argue that the minimum sample size adequate for analysis is generally 100 to 150 participants. Another approach is to consider model complexity in terms of the ratio of the sample size to the number of free parameters to be estimated in a model. A minimum sample size is at least 10 times the number of free model parameters (Raykov & Marcoulides, 2006). For example, a model with 30 free parameters would require at least 300 observations (30×10). Nevertheless, as the authors of the aforementioned articles emphasize, these are only rough guidelines. This is particularly because the requisite sample size depends on numerous factors, including the number and patterns of missing data, strength of the relationships among the indicators, types of indicators (e.g., categorical or continuous), estimation methods (e.g., [robust] maximum likelihood, robust weighted least squares), and reliability of the indicators. Complex issues surrounding sample size determination seem to hamper creating definitive rules –

or even rules of thumb – concerning necessary sample size (e.g., Mundfrom, Shaw, & Ke, 2005).

Instead of elaborating on general guidelines for sample size, more empirically grounded, individual-model-focused approaches to determining sample size in relation to parameter precision and power have been proposed. These approaches include Satorra and Saris (1985), MacCallum, Browne, and Sugawara (1996), and Muthén and Muthén (2002). The methods of both Satorra and Saris (1985) and MacCallum et al. (1996) estimate sample size in terms of the precision and power of an entire model using the chi-square statistic and RMSEA, respectively. In contrast, Muthén and Muthén (2002) evaluate sample size in terms of the precision and power of individual parameters in a model, while allowing the modeling of various conditions that researchers frequently encounter in their research, such as non-normality or type of indicator. Such modeling flexibility is certainly useful for estimating sample size, given that sample size and many variables affect each other in intricate ways.

In order to evaluate sample size, Muthén and Muthén (2002) use four criteria. First, parameter bias and standard error bias should not exceed |10%| for any parameter in the model. Second, the standard error bias for the parameter for which power is of particular interest should not exceed |5%|. Third, 95% coverage – the proportion of replications for which the 95% confidence interval covers the population parameter value – should fall between 0.91 and 0.98. One minus the coverage value equals the alpha level of 0.05. Coverage values should be close to the correct value of 0.95. Finally, power is evaluated in terms of whether it exceeds 0.80 – a commonly accepted value for sufficient power.

An analysis of the sample size of the current data based on Muthén and Muthén (2002) is presented in Table 5. Columns 2 and 3 show population and sample parameters. Population parameters are unstandardized parameters in Table 3. They are viewed as correct, true parameters from which numerous samples (replications) are generated in each run, and results over the replications are summarized. For example, using these values, the parameter bias for self-assessment measured by mathematics is calculated in the following manner: |0.9130 – 0.910|/|0.910| = 0.00330, or in other words, 0.330%. This is far below the criterion of 10%, thereby suggesting a good estimation of the parameter. The result is presented in Column 4. Column 5 shows the standard deviation of the parameters across replications. Column 6 shows the average of the standard errors across replications. The standard error bias for self-assessment measured by mathematics is |0.0743 – 0.0754|/|0.0754| = 0.01459, or in other words, 1.459%. This is again far below the criterion of 10%, thereby suggesting a good estimation of the parameter. The result is presented in Column 7. In particular, we are interested in the effect of self-assessment and teacher assessment on academic achievement. The standard error biases for these parameters of interest are 0.413% and 0.545%, respectively. Neither exceeds 5%, thereby suggesting a good estimation of the parameter. Column 8 provides the mean square error of parameter estimates, which equals the variance of the estimates across replications plus the squared bias (Muthén & Muthén, 2007). Column 9 shows coverage, or the proportion of replications where the 95% confidence interval covers the true parameter value. The value of 0.947 for self-assessment measured by mathematics is very close to 0.95, thereby suggesting a good estimation of the parameter. The last column shows the percentage of replications for which the parameter is significantly different from zero (i.e., the power estimate of a parameter). Column 10 shows that the power for self-assessment measured by mathematics is 1.000, which exceeds 0.80 and suggests sufficient power for the parameter. Together, these results provide good evidence for parameter precision and power for self-assessment measured by mathematics and suggest that the sample size for self-assessment measured by mathematics is sufficient. The same process is repeated for the remaining parameters. It should be noted that the power for the correlation between self-assessment and teacher assessment is low (0.339; see the last row). This suggests that the current sample size of 450 is not enough to distinguish the correlation from zero. Thus, although the sample size for the current model is adequate overall, the underpowered correlation indicates that caution should be exercised when interpreting it. The Appendix shows the Mplus syntax used for the current analysis.

Table 5. Mplus output for the Monte Carlo analysis to determine the precision and power of parameters

	Population parameter	Sample parameters averaged	Parameter bias	SD of sample parameters	Standard error of sample parameters	Standard error bias	Mean square error of parameters	95% coverage	Power
Self-assessment by									
English	1	1	0	0	0		0	1	0
Mathematics	0.910	0.9130	0.330	0.0754	0.0743	1.459	0.0057	0.947	1.000
Science	0.703	0.7024	0.085	0.0613	0.0609	0.653	0.0038	0.950	1.000
Teacher assessment by									
English	1	1	0	0	0	0	0	1	0
Science	0.736	0.7451	1.236	0.0890	0.0876	1.573	0.0079	0.951	1.000
Mathematics	0.528	0.5318	0.720	0.0662	0.0666	0.604	0.0044	0.953	1.000
Academic achievement by									
English	1	1	0	0	0	0	0	1	0
Mathematics	0.483	0.4811	0.393	0.0613	0.0604	1.468	0.0038	0.945	1.000
Science	0.534	0.5310	0.562	0.0658	0.065	1.216	0.0043	0.947	1.000
Academic achievement On									
Self-Assessment	0.498	0.5025	0.904	0.0726	0.0723	0.413	0.0053	0.949	1.000
Teacher assessment	0.380	0.3810	0.263	0.0734	0.0730	0.545	0.0054	0.945	1.000
Self-assessment With									
Teacher assessment	–0.092	–0.0894	2.826	0.0586	0.0578	1.365	0.0034	0.951	0.339

Note. The column labels were slightly changed from original Mplus outputs to enhance clarity. Self-assessment by English refers to a path from the self-assessment factor to the English variable. Self-assessment with Teacher assessment refers to the correlation between these two factors.

VARIOUS SEM ANALYSES

Various types of models can be analyzed within the SEM framework. In addition to the models presented in Figures 1 and 2, we describe models often used in educational studies: confirmatory factor analysis, multiple-group analysis, and latent growth modeling. First, confirmatory factor analysis is used to examine whether the factor structure of a set of observed variables is consistent with previous theory or empirical findings (e.g., Brown, 2006). The researcher constructs a model using knowledge of the theory and/or empirical research, postulates the relationship pattern, and tests the hypothesis statistically. This reinforces the importance of theory in the process of model building. The models of self-assessment, teacher assessment, and academic achievement in Figures 1 and 2 represent different measurement models and must be verified through confirmatory factor analysis in terms of whether each of the three constructs are well represented by the three measurements of English, mathematics, and science. Unfortunately, each measurement model has only three observed variables, and this results in zero degrees of freedom (6 parameters to estimate – two factor loadings, three measurement errors, and one factor variance – and $3(3 + 1)/2 = 6$ data points). The measurement models cannot be evaluated in the current model specification (see model identification in the Five Steps in an SEM Application above).

Various models can be analyzed using confirmatory factor analysis. For example, the often-cited study Holzinger and Swineford (1939) administered a battery of tests to measure seventh- and eighth-grade students in two Chicago schools. The tests were designed to measure mental ability, hypothesized to comprise spatial, verbal, speed, memory, and mathematics abilities. Although Holzinger and Swineford (1939) did not use SEM, the model closest to the one they hypothesized is shown in Figure 4A, and competing models that we postulated are shown in Figures 4B, 5A, and 5B. Figure 4A shows that mental ability comprises a general ability and five sub-abilities. Figure 4B is similar to Figure 4A but assumes a hierarchical relationship between a general ability and sub-abilities. Figure 5A assumes only a single general ability. Figure 5B hypothesizes no general ability and instead assumes correlated sub-abilities. A series of models can be tested on a single dataset using SEM by comparing model fit indices or using a chi-square difference test (see, for example, Brown, 2006; Shin, 2005).

Second, multiple-group or multiple-sample analysis aims to fit a model to two or more sets of data simultaneously. It allows us to test whether and to what extent measurement instruments (tests and questionnaires) function equally across groups, or, put another way, whether and to what extent the factor structure of a measurement instrument or theoretical construct of interest holds true across groups (e.g., Bollen, 1989). Multiple-group analysis involves testing across the samples whether factor loadings, measurement error variances, factor variances, and factor covariances are the same. Equivalence across groups suggests the cross-

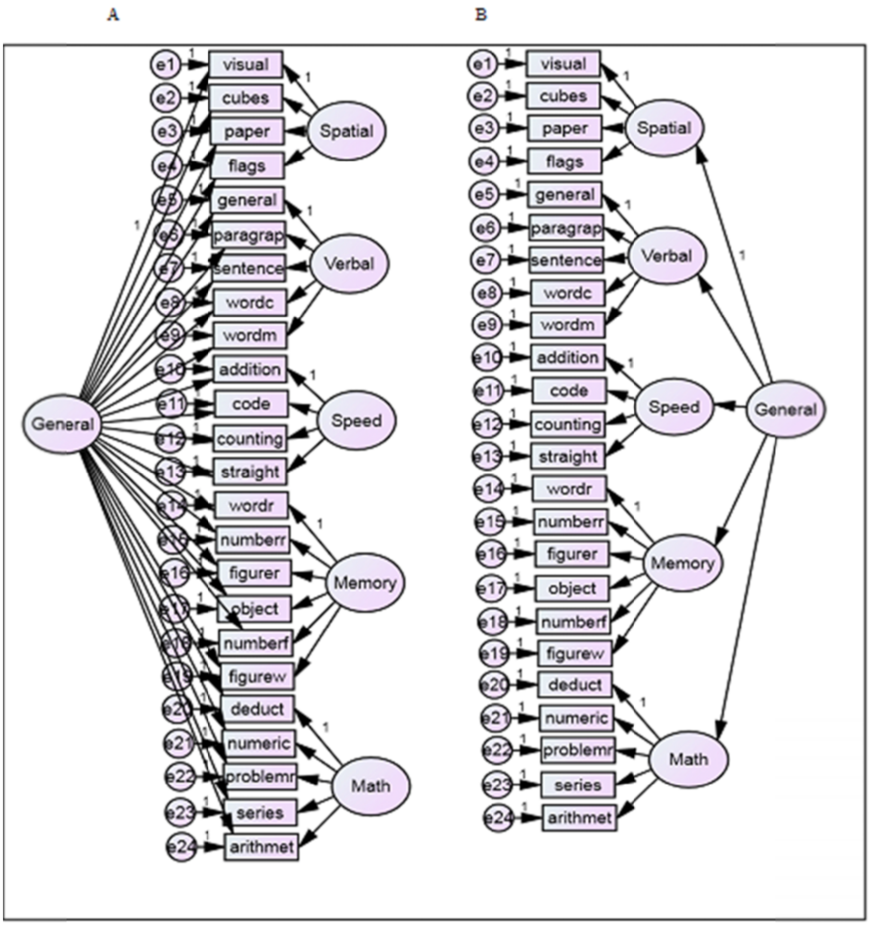

Figure 4. Confirmatory factor analysis of a model of mental ability: Bi-factor model (left) and higher-order model (right). The spatial test battery comprises (1) visual perception, (2) cubes, (3) paper form board, and (4) flags. The verbal test battery comprises (5) general information, (6) paragraph comprehension, (7) sentence completion, (8) word classification, and (9) word meaning. The speed test battery comprises (10) addition, (11) coding, (12) counting groups of dots, and (13) straight and curved capitals. The memory test battery comprises (14) word recognition, (15) number recognition, (16) figure recognition, (17) object-number, (18) number-figure, and (19) figure-word. The math test battery comprises (20) deduction, (21) numerical puzzles, (22) problem reasoning, (23) series completion, and (24) Woody-AcCall Mixed Fundamentals.

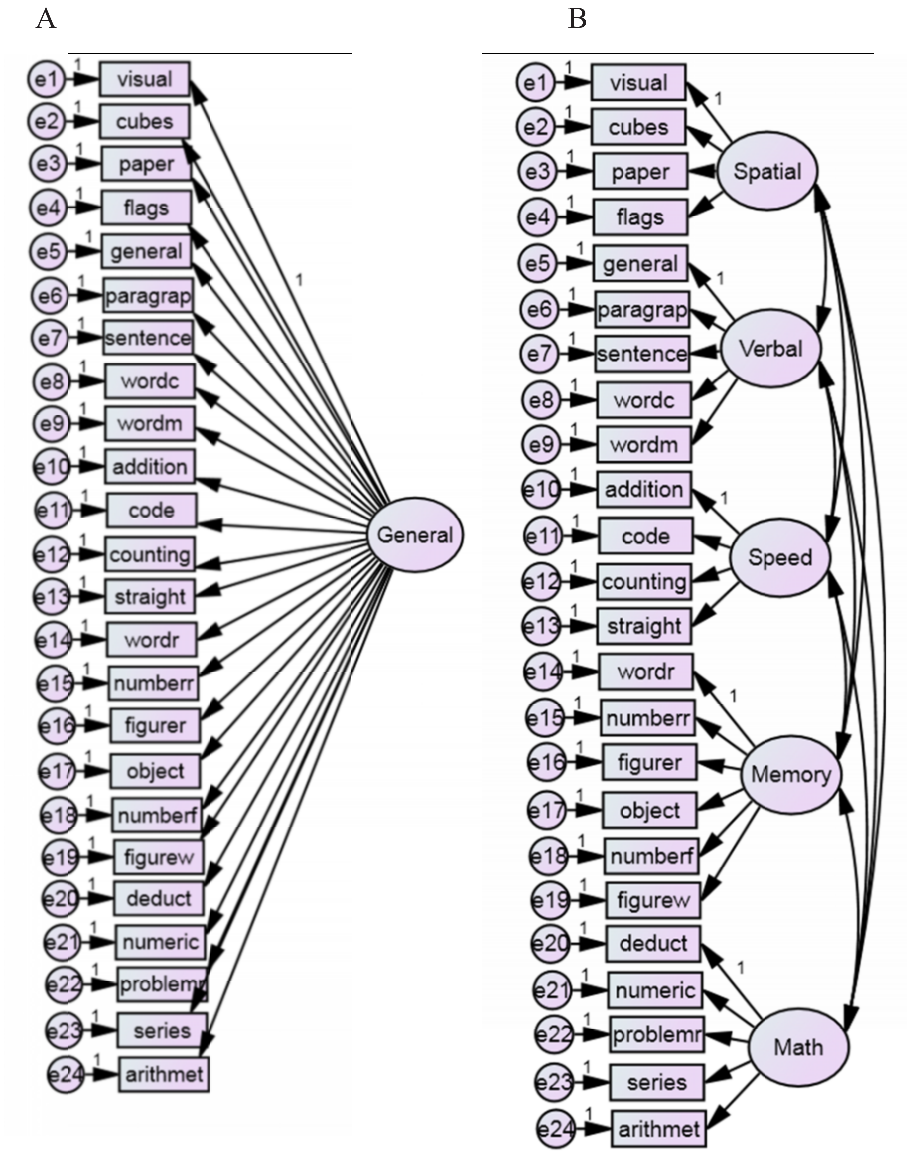

Figure 5. Confirmatory factor analysis of a model of mental ability: Single-factor model (left) and correlated-factor model (right)

validation or generalizability of findings. It is possible that factor loadings are similar in size across groups, while factor covariances are different. For example, Holzinger and Swineford's (1939) data include seventh- and eighth-grade students of both genders from two different schools. It would be of interest to examine whether the bi-factor model of mental ability in Figure 4A is stable across grades, gender, and/or schools. For examples of applications of multiple-group analysis, see Byrne, Baron and Balev (1998), In'nami and Koizumi (2012), and Shin (2005).

Third, latent growth modeling is useful for evaluating longitudinal changes in aspects of individuals over time. It provides a great deal of information, including change at the individual and the group levels, pattern of change (e.g., linear, quadratic), and variables related to change, such as age, gender, motivation, and socioeconomic status (i.e., income, education, and occupation). For example, Tong et al. (2008) hypothesized that second language oral proficiency develops linearly when measured by vocabulary and listening tests at three time points over two years. Their model is presented in Figure 6A. Initial status, also called intercept,

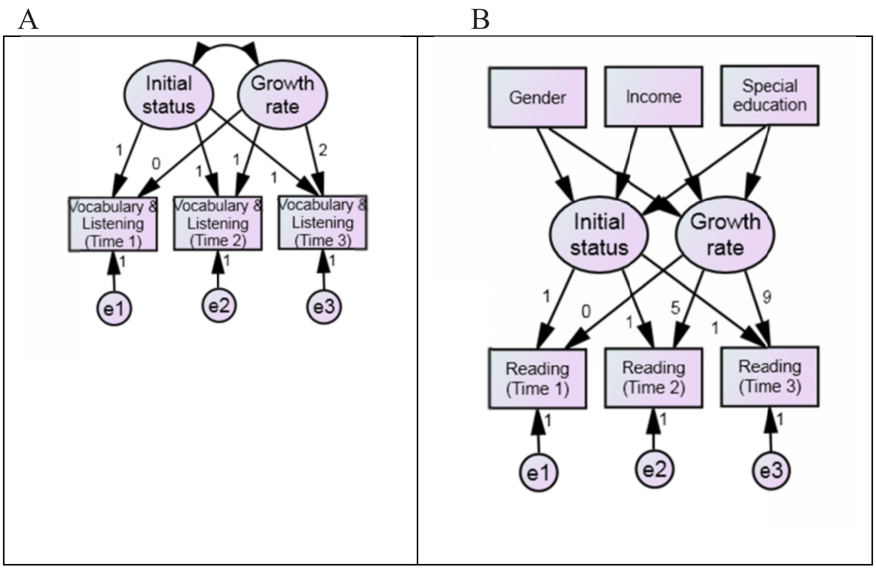

Figure 6. Latent growth model of oral proficiency (left) and of reading proficiency with external variables (right)

indicates the level of proficiency at the beginning of the study. Growth rate, also called slope, indicates the speed at which change is observed at each measurement point. The loadings for the initial status factor are all fixed to be 1, whereas those for the growth rate are fixed to be 0, 1, and 2 to model a linear growth rate. Note that all factor loadings are fixed, unlike confirmatory factor analysis and multiple-group analysis.

More complex models can also be analyzed using latent growth modeling. Yeo, Fearrington, and Christ (2011) investigated how demographic variables – gender, income, and special education status – affect reading growth at school. Their model, shown in Figure 6B, differs primarily from the model in Figure 6A in two ways. First, the loadings for the growth rate factor are fixed to be 0, 5, and 9 – three time points of data collection (August = 0, January = 5, and May = 9) – because we assume that the authors were interested in nine-month growth and rescaled the slope factor loadings accordingly. It should be noted that growth rate factors, whether fixed to be 1, 2, and 3, or 0, 5, and 9, do not change the data-model fit (e.g., Hancock & Lawrence, 2006). Second, the three demographic variables are incorporated into the model as predictors of initial status and growth rate. The results indicate the relative impact of the external variables on the initial level of reading proficiency and on the growth rate of reading proficiency over nine months. For further examples of latent growth modeling, see Kieffer (2011) and Marsh and Yeung (1998).

SOFTWARE

Since Byrne (2012a) provides a detailed, comparative review of SEM software, we will present only a brief treatment of SEM software programs (also see Narayanan, 2012). There are several major commercial programs for performing SEM, including Amos (Analysis of Moment Structures; Arbuckle, 1994-2012), CALIS (SAS Institute, 1990-2012), EQS (Equations; Bentler, 1994-2011), LISREL (Linear Structural Relationships; Jöreskog & Sörbom, 1974-2012), and Mplus (Muthén & Muthén, 1998-2012). Free programs are also available, including Mx (Neale, Boker, Xie, & Maes, 2003) and three R-language packages: the OpenMx package (Boker, Neale, Maes, Wilde, Spiegel, Brick, et al., 2007-2012), the "sem" package (Fox, Nie, Byrnes, Culbertson, Friendly, Kramer, & Monette, 2012), and the "lavaan" package (Rosseel, 2012). The choice of software depends on the purpose of the SEM analysis and the proficiency of the user's computing skills. Byrne (2012a) indicates three aspects related to deciding on the best software: (a) familiarity with SEM concepts and application, (b) the types of SEM model to be tested, and (c) preference concerning manual or graphic interface. She argues that beginners may find Amos or EQS the easiest to use, and that more advanced learners may prefer to use EQS, LISREL, or Mplus. Unlike Amos, EQS, and LISREL, Mplus requires command-based inputs, and learners who are used to graphic interfaces may need some time to become comfortable with the program. In order to familiarize themselves with software, novice learners are referred to Byrne (1998, 2006, 2010, 2012b), whereas advanced learners wishing to use R-based packages are referred to Fox, Byrnes, Boker, and Neale (2012).

SOME DIRECTIONS FOR LEARNING MORE ABOUT SEM

Since SEM is a versatile technique, a single book chapter would not be able to cover a wide range of analyses that can be modeled using SEM. In order to deepen learning regarding SEM, we recommend reading through Byrne (1998, 2006, 2010, 2012b) for LISREL, EQS, Amos, and Mplus, trying to analyze the accompanying datasets, and ensuring that one can replicate findings. Based on our own experience with Byrne (2010) for Amos, and Byrne (2006) for EQS datasets, as well as on discussion with skilled SEM users, we believe that this is probably the best approach to familiarize oneself with SEM and apply the techniques to one's own data.

For providing answers to questions that may arise with regard to particular issues related to SEM, the following recent references may be useful: Bandalos and Finney (2010), Brown (2006), Cudeck and du Toit (2009), Hancock and Mueller (2006), Hoyle (2012), Kaplan (2009), Kline (2011), Lomax (2010), Mueller and Hancock (2008, 2010), Mulaik (2009), Raykov and Marcoulides (2006), Schumacker and Lomax (2010), Teo and Khine (2009), and Ullman (2007). For more on how researchers should report SEM results, see Boomsma, Hoyle, and Panter (2012); Gefen, Rigdon, and Straub (2011); Jackson, Gillaspy Jr., and Purc-Stephenson (2009); Kahn (2006); Kashy, Donnellan, Ackerman, and Russell (2009); Martens (2005); McDonald and Ho (2002); Schreiber, Nora, Stage, Barlow, and King (2006); and Worthington and Whittaker (2006). Reporting a correlation matrix with means and standard deviations is strongly recommended as this allows one to replicate a model, although replication of non-normal and/or missing data requires raw data (for example, see In'nami & Koizumi, 2010). Of particular interest is the journal *Structural Equation Modeling: An Interdisciplinary Journal* published by Taylor & Francis, which is aimed at those interested in theoretical and innovative applied aspects of SEM. Although comprising highly technical articles, it also includes the Teacher's Corner, which features instructional modules on certain aspects of SEM, and book and software reviews providing objective evaluation of current texts and products in the field.

For questions pertaining to particular features of SEM programs, user guides are probably the best resource. In particular, we find the EQS user guide (Bentler & Wu, 2005) and manual (Bentler, 2005) outstanding, as they describe underlying statistical theory in a readable manner as well as stepwise guidance on how to use the program. A close look at manuals and user guides may provide answers to most questions. LISREL and Mplus users should take full advantage of technical appendices, notes, example datasets, and commands, which are all available online free of charge (Mplus, 2012; Scientific Software International, 2012). The Mplus website also provides recorded seminars and workshops on SEM and a schedule listing of upcoming courses.

For problems not addressed by the abovementioned resources, we suggest consulting the Structural Equation Modeling Discussion Network (SEMNET). It was founded in February 1993 (Rigdon, 1998) and archives messages by month. Because of the large number of archived messages collected over the past two decades (thanks to the mushrooming popularity of SEM across many disciplines), SEMNET is a treasure trove of questions and answers on virtually every aspect of SEM. Questions should only be posted if answers to them cannot be found in the archive. As with any other academic online discussion forum, contributors to SEMNET take questions seriously and spend precious time responding to them. We recommend that anyone wishing to receive a good reply should mention that answers were not found in the archive and articulate problems in enough detail for others to respond. Posting a command/script/syntax file is a good idea.

SEM is constantly evolving and expanding. The development and application of new techniques are causing numerous academic disciplines to move increasingly toward a better understanding of various issues that require tools that are more precise. SEM analysis offers powerful options for analyzing data from educational settings, and techniques discussed in this chapter will enable educational researchers to be in a better position to address a wide range of research questions. By employing SEM analysis appropriately, we will be able to contribute much in years to come.

APPENDIX

Mplus Input for the Monte Carlo Analysis for Determining the Precision and Power of Parameters

```
TITLE:          THREE-FACTOR, NORMAL DATA, NO MISSING
MONTECARLO:
                NAMES ARE X1-X9;
                NOBSERVATIONS = 450; ! SAMPLE SIZE OF INTEREST
                NREPS = 10000;
                SEED = 53567;
MODEL POPULATION:
                f1 BY X1@1 X2*.91 X3*.70;
                f2 BY X4@1 X5*.74 X6*.53;
                f3 BY X7@1 X8*.48 X9*.53;
                X1*.77; X2*.37; X3*.61; X4*.91; X5*.48; X6*.76; X7*.66; X8*.63;
                X9*.66;
                f1*.88; f2*.94; f3*.74;
                f3 ON f1*.50; f3 ON f2*.38;
                f1 WITH f2*-.09;
MODEL:
                f1 BY X1@1 X2*.91 X3*.70;
                f2 BY X4@1 X5*.74 X6*.53;
                f3 BY X7@1 X8*.48 X9*.53;
                X1*.77; X2*.37; X3*.61; X4*.91; X5*.48; X6*.76; X7*.66; X8*.63;
                X9*.66;
                f1*.88; f2*.94; f3*.74;
                f3 ON f1*.50; f3 ON f2*.38;
                f1 WITH f2*-.09;
ANALYSIS:       ESTIMATOR = ML;
OUTPUT:         TECH9;
```

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PART II

STRUCTURAL EQUATION MODELING IN LEARNING ENVIRONMENT RESEARCH

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3. TEACHERS' PERCEPTIONS OF THE SCHOOL AS A LEARNING ENVIRONMENT FOR PRACTICE-BASED RESEARCH: TESTING A MODEL THAT DESCRIBES RELATIONS BETWEEN INPUT, PROCESS AND OUTCOME VARIABLES

INTRODUCTION

Learning environments research has a long tradition in investigating perceptions of students and teachers of all kinds of in-school and out-of-school learning environments (Fraser, 1998, 2002, 2007). Interestingly, the vast majority of these studies has investigated student perceptions of teacher behavior or the learning environment, and related such perceptions to student outcomes, either via traditional analyses of variance, multilevel analyses, and, in exceptional cases, structural models. Much less is known about teacher perceptions, let alone teacher perceptions of their own behavior and learning in relation to teacher learning outcomes. The present study thus attempts to fill this blank spot, by focusing on teachers' perceptions of their own behavior and outcomes with respect to conducting practice-based research, and of the school as a learning environment for conducting such research. In addition, rather than variance analyses, the study employs structural equation modeling as a method to link the various variables of interest. In doing so, it enables to investigate the relative importance of these variables in relation to outcomes, but also the processes involved, whether they are about direct connections or not.

In-school practice-based research is commonly seen by researchers, teacher educators and policy makers as an important activity for the professional development of both experienced and prospective teachers (Cochran-Smith & Lytle, 2009; Zeichner & Noffke, 2001). It is expected that teachers who investigate practical problems and examine questions resulting from their own daily practice actively construct knowledge about or gain insight into their own or shared educational practice (Cochran-Smith & Lytle, 1999a; Fenstermacher, 1994). It is assumed that via practice-based research teachers can more effectively improve their educational practice, which ultimately will lead to improvement of pupil learning as well as school development (Teitel, 2003). Both student teachers and experienced teachers have to acquire the teacher-researcher role, which differs from their regular teaching role. Recently, secondary education schools, in particular professional development schools (PDSs), have established research

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 55–74.

environments supportive and stimulative for practice-based research through teachers and student teachers in their schools (NCATE, 2001; Teitel, 2003). PDSs or research oriented schools have been established in several countries, such as Canada, Australia, England, and the USA (Harris & van Tassel, 2005), but also in the Netherlands (Meijer, Meirink, Lockhorst, & Oolbekking-Marchand, 2010; Snoek & Moens, 2011).

In many studies, investigating teacher research in PDSs (for example Snow-Gerono, 2005) as well as studies on teacher action research (for example Ponte, 2002b) or practice-based research (for example Cochran-Smith & Lytle, 2009), the influence of performing practice-based research leading to certain research outcomes within a context containing stimulating or hindering factors is *assumed*, but the actual relationship between such variables is most times not empirically explored. In several studies, research outcomes are reported, but the manner in which they can be explained by other influencing variables such as the research context in schools or the practice-based research process itself is not investigated.

In the present study, relations between teachers' perceptions regarding practice-based research were investigated. These perceptions were measured by means of a questionnaire, developed via two earlier studies conducted by the authors (Vrijnsen-de Corte, 2012).

This study will focus on (student) teachers' perceptions with respect to: (*a*) the learning environment for research at the school ('contextual input'), (*b*) the motives for performing practice-based research ('personal input'), (*c*) the satisfaction of teachers with performed research activities ('process'), and (*d*) the (learning) outcomes that result from these research activities ('outcomes'). By means of analyzing questionnaire data and testing a hypothetical (structural equation) model, we will gather (1) empirical support for assumed relations between concepts associated with practice-based research, and (2) insight into the relative importance of these different concepts in explaining research outcomes. Deeper insight into the relations between (teachers' perceptions of) the input, process and outcomes of practice-based research and the relative strength of these relations, can suggest directions for the successful realization of practice-based research as a professional learning activity in schools.

THEORETICAL FRAMEWORK

Aspects of Practice-Based Research in PDSs

Prior studies on practitioner research in schools suggest different variables that play an important role in the realization of (student) teachers' practice-based research in secondary education schools. In the next section, we will describe these input (contextual and personal), process and outcome related variables and their interconnectedness, more deeply.

Contextual input (research environment in schools). A first important element with respect to the environment for practice-based research is the establishment of a supportive research structure in schools. Conditions such as a research budget, scheduled hours for the benefit of carrying out the practice-based research project, available physical resources and time for discussing, sharing, and performing practice-based research and its results, and accessible resources such as books and journals, seem important preconditions for successful, practice-based research through teachers in schools (Darling-Hammond, 2005). Another important aspect is the position of practice-based research in school policy (Cochran-Smith & Lytle, 2009) for example the integration with existing educational innovations in the school organization or with the training of student teachers. Furthermore, teachers' practice-based research activities are regarded most successful when they are embedded in 'professional learning communities' (Cochran-Smith & Lytle, 1999b; Groundwater-Smith & Dadds, 2006), in which teacher-researchers as well as student teachers can expand their knowledge and skills in a critical dialogue with their colleagues as 'critical friends'.

Second, a *research culture* conducive to the development of professional learning communities and collaboration is an important element with respect to the performance of practice-based research (Ebbutt, 2002; Schussler, 2006; Snow-Gerono, 2005). Besides a shift from traditional isolation to community and collaboration in schools, teachers' professionalism or their willingness to conduct and be actively involved in research, and teachers' recognition of the value of practice-based research, are, according to Ebbutt (2002), important for realizing supportive research cultures in schools. Not only teacher-researchers' engagement in practice-based research is important in this respect, but also the appreciation of colleagues for emerging research initiatives, and the actual use and dissemination of research and research results in the school organization and partnership.

Third, in the establishment of a productive research environment in schools, the *supportive leadership* of the school leader plays an important role (Krüger, 2010). Principals need to motivate teachers and stimulate them to investigate questions and search for solutions to problems resulting from their own or shared educational practices. Therefore, not only a school policy supportive for carrying out practice-based research through teachers needs to be in place, but also a policy that links teacher research to school practice in a way that research and research results can actually enable improvement and innovation (Ebbutt, 2002). This also entails establishing clear requirements for and high expectations of teacher-researchers, directed at monitoring research progress and the control of research quality. Prior research by the authors has shown that teachers hardly seem to distinguish between on the one hand 'research culture' or supportive leadership with respect to the realization of a research supportive culture and on the other hand 'research infrastructure' or supportive leadership with respect to the realization of conditions supportive and/or stimulative for practice-based research (Vrijnsen-de Corte, 2012).

Fourth, to create professional space for experienced teachers' embedded professional development and prospective teacher learning through (collaborative) practice-based research, professional development schools work together in *partnerships* with other schools and/or teacher education institutes (Conaway & Mitchell, 2004; Cornelissen, van Swet, Beijaard, & Bergen, 2011; Cooner &

Tochterman, 2004; Darling-Hammond, 2005; Snow-Gerono, 2005). Within these partnerships collaborations among and across teacher-researchers, their critical colleagues, the participants in the practice-based research projects, academic researchers, teacher educators and so on, can take many forms.

In different studies investigating (student) teachers' practice-based research in schools, teachers and student teachers have mentioned the presence of a research culture (Worrall, 2004) and research infrastructure (Worrall, 2004; Watkins, 2006) and the way in which these are realized in schools, as important preconditions for performing practice-based research. Most times, different contextual aspects together (research culture, research infrastructure and supportive leadership) were mentioned as prerequisite; partnership emerged as a concept unique for the PDS in these studies. However, while several studies have investigated (student) teachers' perceptions of practice-based research within the PDSs context (Mule, 2006; Levin & Rock, 2003), the influence of factors such as the partnership on the actual research process and outcomes following (student) teachers' practice-based research activities, has less frequently been investigated. In this study, the three contextual input variables included are: 'research culture', 'research infrastructure' (both including some aspects of supportive leadership), and 'partnership'.

Personal Input (Teachers' Research Motivation)

In the literature, several goals or expected outcomes are proposed for teachers' practice-based research. By means of carrying out practice-based research, teachers are assumed to deepen their understanding of own (or shared) educational practice, including pupil learning and learning results (Cochran-Smith & Lytle, 2009; Ponte, 2005). It is expected that teachers, through conducting practice-based research activities, can acquire deep practical knowledge about the causes and consequences of their actions, find answers to their specific practical problems, and provide evidence about what works in practice and why (Cochran-Smith & Lytle, 2009; Cordingley, 2003; Ponte, 2005). Based upon their developed practical knowledge and the results of their practice-based research projects, teachers can improve, evidence-based, their own or shared educational practice and solve practical problems in their classrooms and/or school organization (Elliott, 2008). These intended results of practice-based research activities, form important *motives* for teachers to conduct practice-based research in their schools (see for example Worrall, 2004 and Watkins, 2006). Worrall (2004) states the concept of personal development features in most teachers' accounts of the reasons behind their involvement in research. However, the relations between certain motives for performing practice-based research and the actual performance of the research process or the gathered research outcomes have not been investigated. Therefore, teachers' 'research motives' are included in this study as an important personal input variable.

Practice-based Research Process (Research Activities)

In different phases of their practice-based research projects teachers perform various research activities. In the literature, several models for teachers' research processes have been described, with approximately the same concepts and elements (Burton & Bartlett, 2005; Hubbard & Power, 1993; 1999; Lankshear & Knobel, 2004; Mills, 2000; Ponte, 2002a). First, activities can relate to the exploration and definition of the research problem(s) and question(s), resulting in a proposed research plan or, in other words, the 'planning' of the practice-based research. Second, activities can refer to the realization of the proposed research plan, such as collecting and analyzing research data or, in other words, 'performing' the practice-based research. Third, activities can concern the evaluation of the carried out practice-based research or, in other words, 'evaluating' the practice-based research. Fourth and last, activities can be undertaken making the research and research results public or, in other words, 'reporting' the practice-based research. Within a research cycle, the different research activities are supposed to follow up each other (Ponte 2002a). Prior research conducted by the authors showed that teachers mainly make a distinction between planning and performing practice-based research and the 'more finalizing' activities such as evaluating and reporting (see Vrijnsen-de Corte, 2012). In most studies on (student) teachers' practice-based research, perceived (learning) outcomes have been investigated, both with respect to performing research as well as with respect to teaching (Levin & Rock, 2003; Henson, 2001; Zeichner & Noffke, 2001), but most times not in relation to the actual research process itself (and the performed research activities). Therefore, in this study two process variables are included: 'planning and performing research' and 'evaluating and reporting research'.

(Learning) Outcomes (Teachers' Professional Growth)

Practice-based research is assumed to stimulate teachers' knowledge, beliefs and practices, both with respect to teaching and student learning as well as with respect to conducting research (Ponte, Ax, Beijaard, & Wubbels, 2004). Conditional for doing and using practice-based research through teacher-researchers are their positive attitudes towards research (cf. Kirkpatrick & Kirkpatrick, 2006) and their appreciation of its benefits (cf. Kincheloe, 2003). Both influence the extent to which teachers perceive their role as researchers as meaningful as well as the extent to which they will learn. This *research attitude* refers to teachers' evaluative quality – like or dislike of practice-based research – (Shrigley, Koballa, & Simpson, 1988), including terms such as interest, enjoyment, and satisfaction (Gardner & Gauld, 1990) and even curiosity, confidence, and perseverance (Shulman & Tamir, 1972). It is assumed that these attitudes in turn determine teachers' efficacy beliefs with respect to performing practice-based research activities.

Research has shown that in order for teachers to change or improve their behavior related to their teaching practice, it is important that teachers believe they can achieve these changes (Bandura, 1997). Research efficacy beliefs are thus conditional for performing research as well as for achieving the actual outcomes of teachers' practice-based research projects. Research has also shown relevant distinctions between various types of efficacy beliefs, such as general teaching efficacy belief and personal efficacy belief (Gibson & Dembo, 1984). In our prior research it was found that in teachers' perceptions only a meaningful distinction could be made between research-related outcomes or, in other words, 'research attitude and efficacy beliefs' and teaching-related outcomes or, in other words, 'teacher efficacy' (see Vrijnsen-de Corte, 2012). In this study we therefore included these two outcome variables.

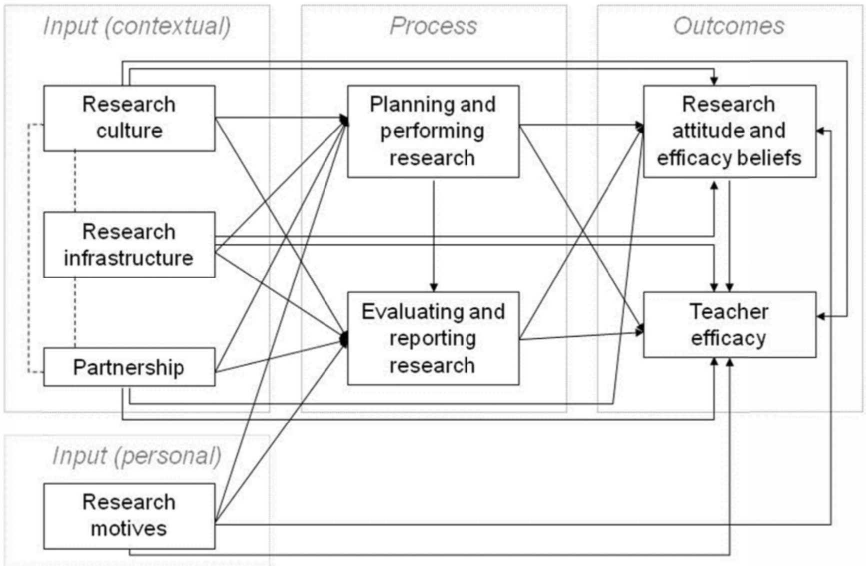
Relations between Input, Process and Outcomes

In conclusion, it can be stated that many assumptions regarding relations or influences between aspects associated with (student) teachers' practice-based research in schools, have not (yet) been supported with empirical evidence. If aspects and their interrelations were investigated, this most times happened between specific pairs or parts of the variables discussed; a complete test of relations between the context, process and outcome variables has – at least to our knowledge – not yet been conducted. This study is directed at this more encompassing test of associations between variables as perceived by teachers and student teachers. The assumed relations as described in the theoretical framework and the starting points of our research are presented in the hypothetical starting model visualized in Figure 1.

Research Questions

The main question investigated in this study is: What model explains the empirical relations that exist in (student) teachers' perceptions of factors associated with the input (contextual and personal), process and outcomes of in-school practice-based research? This resulted in the following more specific sub questions:

1. What relations exist between (student) teachers' perceptions of input (context and personal), process and outcome variables?
2. What empirical model explains these relations (e.g. fits the data)?
   a. What direct and indirect relations exist in this empirical model between (student) teachers' perceptions of the input, process and outcomes of practice-based research?
   b. What relative importance do different input and process variables have on outcomes of practice-based research?



Note: '→' signifies direct relations, '---' means an association between variables rather than a causal relation

Figure 1. Hypothetical starting model

METHOD

Respondents

For the benefit of analyzing relations between variables associated with practice-based research in schools by means of structural equation modeling (SEM), data was gathered from 102 (student) teachers. Only respondents who answered items for all variables in the questionnaire – so, including the partnership variable that is only present in PDSs or teacher education practice schools – were included in the analysis. Data of a total of 56 respondents could be included in the study: 39 were experienced teachers and 17 were student teachers. The experienced teachers participating in this study had finished (or almost finished) practice-based research as a professional learning activity in their schools. These teachers taught different school subjects and worked 27.6 hours per week on average (SD = 10.3). Most of the teachers in the sample had between 20 and 30 years teaching experience since graduation. The student-teachers who carried out practice-based research as a part of their teacher training were in their graduation year of their curriculum and were working in one of the participating schools as part of their teacher training. These student teachers were also teaching different subjects.

Table 1. Domains, scales, number of items, Cronbach's alpha (CA), and sample items for the QTR scales

Domain	Scale	Items	CA	Sample item
Input				
	Environment			
	Research culture[1]	7	0.81	'At our school, teachers' practice-based research is taken for granted'
	Research infrastructure[1]	5	0.71	'At our school, the school leader showed interest in my practice-based research'
	Partnership[1]	8	0.90	'Our school makes a contribution to the research partnership'
	Personal			
	Research motives[1]	5	0.74	'I conduct practice-based research because I want to gather more insight into pupils' (learning) needs'
Process				
	Planning and performing research[2]	10	0.84	'During the planning phase of my practice-based research, I have made a research plan'
	Evaluating and reporting research[2]	15	0.92	'During the evaluation phase of my practice-based research, I have discussed the conclusions of my research with colleagues'
Outcomes				
	Research attitude and efficacy beliefs[3]	14	0.93	'Resulting from my practice-based research, I now enjoy conducting practice-based research'
	Teacher efficacy[3]	15	0.95	'Resulting from my practice-based research, I am now directed at improving pupils' education'

Notes: [1]5-point Likert-scale (1 = not or in a very small extent, 5 = in a very high extent)
[2]4-point scale (1 = not performed at all, 2 = weak performed, 3 = medium performed, 4 = very well performed)
[3]5-point Likert-scale (1 = much smaller/more badly, 5 = much more/ much better)

Instrumentation

Based upon the findings of an interview study (see Vrijnsen-de Corte, 2012), the Questionnaire on Teacher Research (QTR) was developed in order to map (student) teachers' perceptions. The instrument is a self-report questionnaire used to assess teachers' perceptions concerning practice-based research in schools. The questionnaire consisted of eight scales with a total of 79 statements to be rated. In Table 1, the eight scales, their corresponding number of items, the Cronbach's alpha's (CA) as well as some example items, are displayed.

Regarding the contextual input (environment), the 'research culture' scale measured teachers' perceptions of the school support by colleagues and school leaders for practice-based research in their schools. The 'research infrastructure' scale asked for teachers' perceptions of the existing organizational structure, including conditions such as research budget, available resources, and supportive school policy for performing practice-based research in their schools. The 'partnership' scale measured teachers' perceptions of the collaboration of their schools with other partners with respect to practice-based research. The research motives scale (personal input) measured teachers' motives for performing practice-based research. The first process scale, 'planning and performing research', asked for teachers' perceptions of the activities with regard to planning and performing practice-based research. The second process scale, 'evaluating and reporting research', measured teachers' perceptions of the activities with respect to the evaluation and report of the practice-based research. The first outcome scale, 'research attitude and efficacy beliefs', mapped teachers' perceptions of the outcomes of their practice-based research with respect to performing research: changed research attitude, and improved/reduced research knowledge and skills. Last, the second outcome scale, 'teacher efficacy', measured teachers' perceptions of the outcomes of their practice-based research with respect to teaching (their self-efficacy beliefs). The Cronbach's alpha's (CA) of the eight scales varied from 0.71 to 0.95. The results showed all scales to be reliable (above 0.70).

Data Analysis

In order to gain insight into the presence of the eight variables in the present sample, a descriptive analysis was conducted. Average scale scores and standard deviations were calculated using SPSS. In addition, Pearson correlations between the QTR-scales were calculated. In order to further investigate the relations between the perceived aspects of teachers' practice-based research in secondary education schools (e.g. the QTR scales), a structural model using MPlus (Muthén & Muthén, 1999) was tested. The data of the aforementioned 56 respondents were used for the modeling process. In the hypothetical starting model (see Figure 1), relations were assumed between the contextual variables research culture, research infrastructure and partnership. These contextual variables, teachers' research motives and the two process variables (planning and performing research, and evaluating and reporting research), were hypothesized to affect teachers' research attitude and efficacy beliefs, as well as teacher efficacy. The two process variables were assumed to be affected by the contextual variables and teachers' research motives. The first process variable 'planning and performing research' was assumed to effect the second process variable 'evaluating and reporting research'. Last, teacher efficacy was hypothesized to be affected by teachers' research attitude and efficacy beliefs.

Fit indices showed the hypothetical starting model to fit the data well ($\chi 2$ = 1.179 with df = 3 (p=.76); the Comparative Fit Index (CFI) =1.00; the Tucker Lewis Index (TLI) =1.00; Root Mean Square Error of Approximation (RMSEA) =.00; Standardized Root Mean Square Residual (SRMR) =.03; see Table 2, model 1). While the hypothetical model fitted the data, many of the relations tested in this structural model were weak and statistically non-significant. Through excluding these non-significant relations from the model (given the one-directionality assumed in the relations, these were tested one-sided (at p =.05)), a more economic parsimonious structural model emerged. The final structural model also provided an adequate fit to the data ($\chi 2$ = 16.17 with df = 18 (p=.58); CFI=1.00; TLI=1.00; RMSEA=.00; SRMR=.08; see Table 2, model 2). Thus, the difference between model and data was non-significant: CFI and TLI were above the required value of .95. However, SRMR was above the required value of .05 indicating that there was some unexplained variance in the model. The standardized path coefficients and effect sizes (Cohen's effect size for correlation) were estimated for the final model.

Table 2. Model fit measures

Description	X^2	(df)	P-value	CFI	TLI	RMSEA	SRMR
Model 1 Hypothetical starting model	1.18	3	.76	1.00	1.00	.00	.03
Model 2 Final empirical model	16.17	18	.58	1.00	1.00	.00	.08

X^2 describes the distance between model and data, but depends on the sample size. CFI and TLI describe the 'power' of the model compared to 'the situation without the model'. SRMR and RMSEA describe how much error or unexplained variance remain after fitting the model.

RESULTS

Teachers' Perceptions of Practice-based Research (RQ1)

In Table 3, average scale scores, standard deviations, and Pearson correlations for the eight QTR scales are presented. The results show that for all QTR scales,

Table 3. Average scale scores, standard deviations, and Pearson correlations between QTR scales

Domain	Scales	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input (contextual)	(1) Research culture	3.10 (.68)	-							
	(2) Research infrastructure	3.04 (.86)	.48#	-						
	(3) Partnership	2.93 (.96)	.54#	.59#	-					
Input (personal)	(4) Research motives	3.88 (.70)	.20	.21*	.12	-				
Process	(5) Planning and performing research	2.98 (.57)	.11	.13	.18	.17	-			
	(6) Evaluating and reporting research	2.38 (.73)	.17	.54#	.37#	.14	.35#	-		
Outcomes	(7) Teacher efficacy	3.43 (.68)	.22*	.13	.12	.56#	.31#	.11	-	
	(8) Research attitude and efficacy beliefs	3.54 (.64)	.28#	.38#	.37#	.53#	.33#	.39#	.68#	-

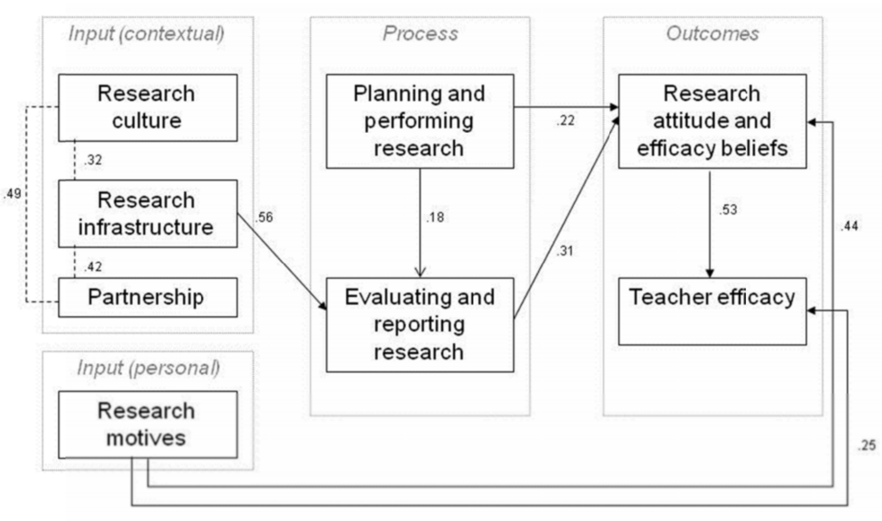
*Note: # $p < .01$, * $p < .05$*

except for the evaluating and reporting scale, respondents on average scored above the scale mean. Respondents scored highest with respect to the research motives scale. Also, regarding both outcome scales ‘research attitude and efficacy beliefs’, and ‘teacher efficacy’, respondents on average scored rather high. The respondents were somewhat positive with respect to the three context scales and the planning and performing research scale. With respect to the evaluating and reporting research scale, respondents scored medium/neutral (just below the scale medium). On average, the variance in respondents' scores was moderate. The partnership scale had the largest variance of all the eight scales, suggesting that, respondents varied most on this scale in their responses. Also the research infrastructure scale had a large variance, suggesting considerable differences between teachers and schools. For the planning and performing research scale, the smallest variance was found.

Pearson correlation coefficients (see Table 3) ranged between .21 and .68. Strong correlations existed between the contextual input scales: between research culture and research infrastructure (.48); research culture and partnership (.54); and research infrastructure and partnership (.59). Also, between research infrastructure and evaluating and reporting practice-based research there was a considerable correlation (.54). Research motives correlated highly with the outcome scales (.56 and .53, respectively). Finally, there was a strong correlation between the two outcome scales (.68).

Structural Relations between Teachers' Perceptions (RQ2)

In Figure 2, the final structural model (model 2) as well as the standardized path coefficients, are depicted.



Note: '→' signifies direct relations, '---' means an association between variables rather than a causal relation

Figure 2. Empirical structural model of significant paths between measured variables

It should be noted, however, that because the date were collected at one moment in time, real causality cannot be tested. Hence, the model merely suggests logical paths between measured variables. The direction of the arrow represents the direction of the causality. Each relation depicted in the figure concerned a statistically significant relation between two variables. Besides all direct effects influencing the two process and outcome variables, several indirect effects occurred. These indirect effects emerged via different pathways in the structural model: for example, partnership has an indirect influence on evaluating and reporting research via research infrastructure but also via research culture (and research infrastructure). The total effects concern a total sum of the direct and indirect effects between two variables. In Table 4, the direct, indirect and total effects (cf. Verschuren, 1991) based upon Figure 2 are displayed. These effects are further explained below.

Table 4. Direct (D), indirect (I), and total effects (T) based on Figure 2

Domain and variables	Process						Outcomes					
	Planning and performing research			Evaluating and reporting research			Research attitude and efficacy beliefs			Teacher efficacy		
	D	I	T	D	I	T	D	I	T	D	I	T
Contextual input												
Research culture	-	-	-	-	.29	.29	-	.09	.09	-	.05	.05
Research infrastructure	-	-	-	.56	-	.56	-	.17	.17	-	.09	.09
Partnership	-	-	-	-	.32	.32	-	.10	.10	-	.05	.05
Personal input												
Research motives	-	-	-	-	-	-	.44	-	.44	.25	.23	.48
Process												
Planning and performing research	-	-	-	.18	-	.18	.22	.06	.28	-	.15	.15
Evaluating and reporting research	-	-	-	-	-	-	.31	-	.31	-	.16	.16
Outcomes												
Research attitude and efficacy beliefs	-	-	-	-	-	-	-	-	-	.53	-	.53
Teacher efficacy	-	-	-	-	-	-	-	-	-	-	-	-

Note: D: means direct effect, I: means indirect effect, and T: means total effect

Direct, Indirect and Total Relations (RQ2a)

Input (contextual and personal) – process. There are no direct or indirect effects of input variables (contextual and personal) on the planning and performing research variable in the structural model. With respect to the contextual input variables, only 'research infrastructure' had a medium direct effect (.56) on 'evaluating and reporting research' (total effect .56). Thus, the greater the presence of a research infrastructure was perceived by teachers, the more satisfied they were with research activities they performed. The other two contextual input variables only had a small indirect effect (via research infrastructure or both other contextual variables and research infrastructure) on 'evaluating and reporting research'. 'Research culture' had an indirect and total effect of .29 and 'partnership' an indirect and total effect of .32 on evaluating and reporting research. The personal input variable 'research motives' did not have an effect (direct or indirect) on 'evaluating and reporting research'.

Process. In the structural model there was a very small relationship between the two process variables. The planning and performing research variable had a direct effect of .18 on the evaluating and reporting research variable (total effect .18). Thus, the more teachers perceived to have been engaged in planning and performing research activities, the more they reported to have been engaged in evaluating and reporting their research.

Process – outcomes. The planning and performing research variable had a small direct effect of .22 as well as a very small indirect effect (via evaluating and reporting research) of .06 on 'research attitude and efficacy beliefs' (total effect .28). The second process variable 'evaluating and reporting research' only had a direct effect of .31 on 'research attitude and efficacy beliefs'. This means that the more teachers perceived their evaluating and reporting research activities as very well performed, the more they perceived improved research attitudes and efficacy beliefs. Both process variables only had an indirect effect on 'teacher efficacy'. The variable 'planning and performing research' had an indirect effect of .15 and the variable 'evaluating and reporting research' had an indirect effect of .16. Thus, the more teachers perceived their planning and performing research activities and their evaluating and reporting research activities as very well performed, the more they perceived increased teacher efficacy.

Input (contextual and personal) – outcomes. Given the aforementioned results, all contextual input variables only had indirect effects on both outcome variables (mainly via research infrastructure). Research culture had an indirect effect of .09, research infrastructure an indirect effect of .17, and partnership an indirect effect of .10 on research attitude and efficacy beliefs. Thus, the more teachers perceived the presence of the research culture, research infrastructure, and partnership at their schools, the more they perceived improved research attitudes and efficacy beliefs. Teacher efficacy was influenced indirectly by research culture (.05), research infrastructure (.09), and partnership (.05). Thus, the more teachers perceived the presence of a research culture, research infrastructure and partnership at their schools, the more they perceived increased teacher efficacy. The personal input variable 'research motives' had a direct effect of .44 on research attitude and efficacy beliefs. This means that the more teachers perceived they had clear research motives, the more they perceived improved research attitudes and efficacy beliefs. With respect to the outcome variable 'teacher efficacy', 'research motives' had a direct effect of .25 as well as an indirect effect via research attitude and efficacy beliefs of .23 (total effect .48). This suggests that the more teachers perceived to have clear research motives, the more they perceived increased teacher efficacy.

Outcomes. Between both outcome variables there was a relationship as shown in the structural model. Research attitude and efficacy beliefs had a direct effect of .53 on teacher efficacy (total effect .53). Thus, the more teachers felt they were capable of conducting research, the more they felt they improved their teaching.

Relative Importance of Variables and Model (RQ2b)

When the above described relations between the variables of practice-based research are compared to each other, the following trends emerged:

1. The influence of the research infrastructure variable on the planning and performing research variable and both outcome variables was two times stronger than that of the other two context variables (and moreover it was the only direct influence).
2. The research motive variable appeared four times more stronger in its effect on outcomes than the other input variables (i.e. contextual input variables); this suggests it can be regarded as more important than all the other context variables together.
3. Both process variables had double the effect on outcomes compared to the context variables. Compared to the research motives variable their effect was half that in size; but process variables did have a direct influence on outcomes.

The variance (*R2)* in evaluating and reporting research was explained for 35% by the three contextual input variables and planning and performing research. The variance in research attitude and efficacy beliefs was explained for 47% by the input variables (contextual and personal) and both process variables. The variance in teacher efficacy was explained for 36% by direct and indirect relations with all other variables.

CONCLUSION AND DISCUSSION

Overall, we found empirical evidence for most of the assumptions (frequently) mentioned in the literature. The developed empirical structural model fitted the data well and explained quite a lot of variance, in particular with respect to the process variable evaluating and reporting research (35%) and both outcome variables (respectively 36% for research attitude and efficacy beliefs, and 47% for teacher efficacy). Furthermore, we have gathered more insight into what (student) teachers themselves think about which concepts are important with respect to practice-based research outcomes in secondary education schools. Based upon the findings of this study we can draw three important conclusions.

First, the contextual input variables had mainly indirect effects on process and outcome variables. Only research infrastructure had a direct influence on the process variable 'evaluating and reporting research. This causal relation was the strongest relation in the total structural model (.56). The other contextual variables 'research culture' and 'partnership' appeared only marginally important and were mediated by 'research infrastructure', process and outcome variables. Based upon this finding we can draw the conclusion that the contextual variables are not that important in explaining teachers' perceptions of the practice-based research process and research outcomes as mentioned in some literature (Holmes Group, 1990; NCATE, 2001).

Second, we can conclude that both process variables do have an important influence on the outcome variables 'research attitude and efficacy beliefs' and 'teacher efficacy'. Both process variables directly influenced the outcome variable 'research attitude and efficacy beliefs'. The planning and performing research variable also had an indirect influence. Both process variables indirectly influenced teacher efficacy, via the mediating variable research attitude and efficacy beliefs. This finding does confirm findings from our prior study (see Vrijnsen-de Corte, 2012), that the practice-based research process (and its quality) is of major importance for obtaining both research outcomes.

Third, research motives have a direct influence on both outcome variables. This influence was up to twice as strong as the influence of the process variables. Based upon this finding we can draw the conclusion that besides the process variables research motives are also very important for obtaining both outcomes.

On the whole, the developed structural equation model seemed promising for investigating (student) teachers' practice-based research in schools. The empirical structural equation model showed several direct and indirect relations between perceived concepts associated with teachers' practice-based research in schools. From the strength of the relations, we can deduce what concepts and what relations between those concepts are relatively important for implementing practice-based research through teachers-as-researchers in secondary education schools.

First, schools that want to implement practice-based research as a professional learning activity, with outcomes regarding performing research as well as regarding teaching, should focus on teachers' and student teachers' motives for performing practice-based research and the practice-based research process itself, instead of investing in and focusing too much on the context for practice-based research in schools (research culture, research infrastructure and partnership). Successfully realizing practice-based research in schools starts with selecting teachers who are *interested* in research (results) and *eager* to perform practice-based research activities. Especially these teachers need to get inspired for researching their own educational practice as a professional learning activity. Therefore, schools should show them 'good practices' and convince them of the added-value of practice-based research activities for the education of pupils and for own professional learning as a teacher. Inspired teachers themselves should formulate the research questions: emerging from their own educational practice and leading to direct and observable improvements. Besides this, schools should show teachers how these good practices are established: what makes that these research projects are successful?

Second, while the context for practice-based research in schools is the most important variable. In the perception of the (student) teachers, research culture and partnership do have a strong coherence with the research infrastructure, but are more indirectly important for the process and outcomes of practice-based research in schools. Schools should thus focus first on realizing in-school structures directly important for performing practice-based research and realizing research outcomes.

The developed empirical structural model does fit the research data well, however, the percentages explained variance for the process and outcome variables of the model still showed some room for improvement. In this structural model we defined all concepts as latent variables due to the small sample size. Hence, measurement error for the different variables could not be accounted for in the model. Further, the question remains if these are the only important concepts or that there are other also important concepts to be taken into account.

Besides this, in this study we investigated (student) teachers' perceptions of the concepts associated with practice-based research in schools via a questionnaire. Therefore, concepts were measured in a prescribed and structured manner, leaving no room for more personal descriptions. If (student) teachers did have a perception of other concepts (which we did not include in our questionnaire) these perceptions were not taken into account. It is also the question if (student) teachers do have a good image of all concepts questioned. The structural relations found in the model were prompted by teachers and student teachers as perceived at this moment. These relations can change in time with the development of practice-based research in schools.

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4. DEVELOPMENT AND VALIDATION OF AN ENGLISH CLASSROOM LEARNING ENVIRONMENT INVENTORY AND ITS APPLICATION IN CHINA

INTRODUCTION AND THEORETICAL FRAMEWORK

Relevant teaching and learning activities need to be conducted in various learning environments, with the classroom being the principal place for teaching most subjects. So, the classroom learning environment has an important influence on the teaching–learning process. Generally speaking, classroom environment refers to various kinds of physical, social and psychological factors that influence teaching activities (Fraser, 1998). China's New English Curriculum Reform is in an important period of implementation. What does the English classroom look like in the context of the new curriculum reform? Students are in a good position to judge their classroom environment because they have experienced a variety of different learning environments and have had sufficient time in the class to form accurate perceptions of their learning environments (Fraser, 2012). Having an understanding of students' perceptions of their English classroom learning environments provides a useful basis for improving classroom teaching and learning. Students' perceptions of the classroom learning environment can be used as a tool for teachers' reflection and as a guide in teachers' attempts at improvement of their classroom environments (Aldridge, Fraser, Bell, & Dorman, 2012).

The beginning of the study of classroom learning environments can be traced back to the work of Herbert Walberg and Rudolf Moos (Fraser, 2012). From then on, research on classroom learning environments has attracted great attention and developed rapidly. The study of the classroom learning environment has focused on the effectiveness of new curricula and teaching approaches, the development of classroom environment instruments, the factors that influence classroom environment, and associations between the classroom environment and student outcomes (academic achievements and attitudes, etc.) (Fraser, 2012). Among these, the development of classroom environment instruments and associations between the classroom environment and students' outcomes have drawn the most attention (Macaulay, 1990). Research has supported that students' perceptions of the classroom environment are significantly related to their outcomes (Fraser & Fisher, 1982). Also researchers have used classroom environment assessments as criteria in evaluating educational programs and innovations (Afari et al., 2013; Lightburn & Fraser, 2007; Nix, Fraser, & Ledbetter, 2005). With the development of research methods and techniques for data collection and data analysis, Western

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researchers have developed several extensively-validated and widely-used classroom learning environment instruments, such as the Learning Environment Inventory (LEI), My Class Inventory (MCI), Science Laboratory Environment Inventory (SLEI), Constructivist Learning Environment Inventory (CLEI) and the popular What Is Happening In this Class? (WIHIC) (Fraser, 2007, 2012; Liu, Ma, & Liu, 2009). Some scales from the WIHIC were used in the present study.

OBJECTIVES AND RESEARCH QUESTIONS

The main purpose of the present study was to develop a learning environments questionnaire for English classrooms in China. Several Western classroom environment instruments, including the WIHIC, CLES and SLEI, have been translated into Mandarin by Taiwanese researchers (Huang, Aldridge & Fraser, 1998). These instruments were found to be valid and useful after being translated into Mandarin. However, the studies also showed that students and teachers had different understandings of the same questions in different languages because of different educational systems based on differences in politics, economies and cultures. The meaning of the original items thus could be different in a translated version.

Chinese researchers have developed classroom environment instruments to suit the cultural mores in China, such as the Hong Kong Classroom Environment Scale (HKCES) that measures the junior high school mathematics classroom learning environment, developed by Hong Kong scholars Lee Chikin John, Lee Lai Mui Frances and Wong Hin Wah (2003), and the My Class Questionnaire developed by the mainland scholar Jiang Guangrong (2004). At the same time, the Teacher–Student Interaction Questionnaire (TSIQ) was developed by the Taiwanese scholar She (1998) to assess interactions between teachers and students.

However, all of these instruments were used for measuring classroom learning environments in science, mathematics or biology. In mainland China, because the English curriculum is undergoing reform, it was timely to develop an instrument which could be used to assess students' perceptions of the English classroom environment in the context of the new curriculum reform.

The other purpose of the present study was to explore associations between the classroom learning environment and students' outcomes in Mainland China. Overall, the research questions that guided the present study were:

1. Is the newly-developed English Classroom Environment Inventory valid and reliable when used with high school students in China?
2. Do students' perceptions of their English classroom learning environments vary with student sex, year level and school province?
3. Are there associations between the classroom learning environment and student outcomes based on their achievement and English learning-related attitudes?

METHODOLOGY

Sample

High school students in Grades 7, 8, 10 and 11 were involved during each of the stages of the development and validation of the inventory. The first version of the instrument was administered to 318 students for the purpose of performing an exploratory factor analysis. The resulting final version of the ECLEI was then administered to 1,235 students.

Development of the ECLEI

The first draft of the ECLEI consisted of 56 items in six scales and obtained by examining extensively-validated classroom learning environment inventories such as the WIHIC, LEI and CLES, and by administering an open-ended questionnaire to students to elicit their general perceptions of their English classroom learning environment. The content of the first draft was face-validated by two English language professors, six high school English teachers and the first author, resulting in a reduction to 37 items in six scales in the second draft of the ECLEI.

Exploratory factor analysis was performed after administering the second draft of the ECLEI to 318 students, resulting in a further reduction to 25 items in five scales after deleting items with factor loadings less than 0.40 on their own scale or more than 0.40 on any other scale. One whole scale was removed using these criteria. A five-point frequency scale was used (1 = Almost Never; 2 = Seldom; 3 = Sometimes; 4 = Often; 5 = Almost Always) to solicit students' responses.

The structure of the ECLEI was further confirmed using the results of confirmatory factor analysis after administering it to a further 1,235 students. The final version of the ECLEI consisting 25 items in five scales is provided in Appendix A. The results of the confirmatory factor analysis are summarized in Table 1. The goodness-of-fit of models was evaluated based on the chi-square test statistic and the Root Mean Square Error of Approximation (RMSEA), Goodness of Fit Index (GFI) and Comparative Fit Index (CFI). The results are summarized in Table 2. According to conventional model fit standards, these results indicate good model fit.

A sample item from each ECLEI scale is provided in Table 3. This table also shows the classification of each ECLEI scale according to Moos' three general dimensions for all human environments: relationship dimensions; personal development dimensions; and system maintenance and change dimensions.

Additional statistical information (namely, the internal consistency reliability) is summarised in Table 3. The acceptable level of reliability for every ECLEI scale attests to the validity of the questionnaire in response to the first research question (concerning whether the newly-developed English Classroom Environment Inventory is valid and reliable when used with high school students in China).

Table 1. Confirmatory factor analysis results for the ECLEI (N=1235)

Item	Factor Loadings Teacher Support	Task Orientation	Student Cohesiveness	Cooperation	Organisation
T1	0.66				
T8	0.64				
T12	0.67				
T17	0.70				
T21	0.65				
T24	0.62				
T25	0.57				
T3		0.62			
T6		0.69			
T9		0.57			
T14		0.67			
T15		0.52			
T18		0.63			
T5			0.51		
T11			0.66		
T16			0.73		
T20			0.71		
T23			0.61		
T4				0.56	
T7				0.56	
T10				0.55	
T19				0.58	
T2					0.71
T22					0.51
T13					0.80
Eigenvalue	7.41	2.0	1.42	1.22	1.07
% Variance	29.6	8.0	5.7	4.9	4.3

Table 2. Summary of goodness-of-fit statistics for the ECLEI (N=1235)

Index	Values
χ^2	1017.28
df	265
χ^2/df	3.84
SRMR	0.046
RMSEA	0.048
NFI	0.90
AGFI	0.92
CFI	0.93
GFI	0.93
IFI	0.93

Table 3. Moos classification and sample item and internal consistency reliability (Cronbach's alpha coefficient) for each ECLEI scale (N=1235)

Scale	Moos Scheme	No. of Items	Sample Item	Alpha Reliability
Teacher Support	R	7	Our English teacher likes us.	0.81
Task Orientation	PD	6	I know the goals for this English language class.	0.81
Student Cohesiveness	R	5	Certain students work only with their close friends.	0.75
Cooperation	PD	4	Most students cooperate equally with other class members.	0.66
Organisation	S	3	Our English class is well organized.	0.74

R: Relationship, PD: Personal Development, S: System Maintenance & Change

Test of English-Related Attitudes

In our study, an eight-item scale adapted from Enjoyment scale of the Test of Science-Related Attitudes (TOSRA) developed by Fraser (1981) to measure students' attitudes to English for our sample of 308 Grade 11 students. The attitude items are provided in Table 4. The information was subsequently used in investigating associations between students' perceptions of the classroom learning environment and their attitudes towards English.

Table 4. Test of English-related attitudes

Item	Item Wording
1	I look forward to English lessons.
2	Lessons in English class are fun.
3	I don't like lessons in English class.
4	English is my favorite subject.
5	Lessons in English class bore me.
6	I enjoy lessons in English class.
7	Lessons in English class are a waste of time.
8	English lessons make me interested in English.

Academic Achievement

The mid-year examination scores for the 308 Grade 11 students were used to assess achievement and to investigate associations between students' perceptions of the classroom learning environment and their academic achievement.

Interviews

Twenty students were selected for follow-up interviews to obtain further information about their perceptions of the English classroom learning environment and their English-related attitudes. Ten teachers were also interviewed to identify factors that influence the English classroom environment and to help to explain the research findings obtained from the questionnaires.

FINDINGS

The findings of the study are presented below in two sections. First, students' perceptions of their English classroom learning environments are reported and research question 2 is answered (What are students' perceptions of their English classroom learning environments based on gender, year level and school province?). Second, associations between students' perceptions of the classroom learning environment, their English-related attitudes, and their academic achievement are reported in response to research question 3 (What are the associations between the classroom learning environment and student outcomes based on their achievement and English learning-related attitudes?).

Students' Perceptions of Their English Classroom Learning Environment

When a total of 1,235 students in Grades 7, 8, 9 and 11 English classes provided their perceptions of their English classroom learning environment, the average item mean for the five ECLEI scales varied from 3.68 to 4.21, suggesting that generally high school students had positive perceptions of their English classroom learning environments. The average item mean for Teacher Support, Organisation, Cooperation, Task Orientation and Student Cohesiveness were 4.21, 4.13, 3.94, 3.80 and 3.68, respectively. (As score of 4 for an ECLEI item corresponds to the response alternative of Often and a score of 3 corresponds to Sometimes.)

Sex Differences in Perceptions of the English Classroom Learning Environment

A comparison of students' perceptions of the English classroom learning environment was undertaken for 571 male students and 664 female students. Results from MANOVA showed that female students' perceptions were generally more positive than those of the males, especially for Student Cohesiveness ($F_{(1,233)}$=6.46, p<0.05) and Cooperation($F_{(1,233)}$=4.22, p<0.01). However, sex differences were small for Organisation ($F_{(1,233)}$=0.55, p>0.05). Figure 1 graphically depicts these sex differences in ECLEI scale scores.

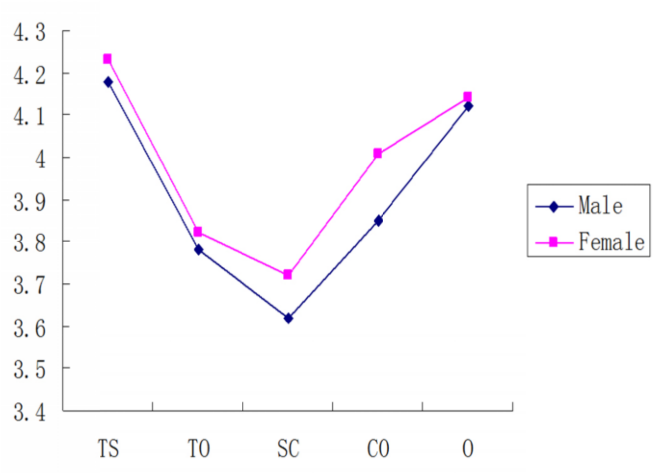

Figure 1. Sex differences in students' perceptions of learning environment (n=571 males and 664 females)

Differences between Grade Levels in Students' Perceptions of the English Classroom Learning Environment

Students' perceptions of the classroom learning environment for different grade levels were analysed using MANOVA and multiple comparisons of means. Results indicated that there were differences in overall responses ($F_{(3,1231)}$=14.09, p<0.01) and for the four scales of Teacher Support ($F_{(3,1231)}$=16.52, p<0.00), Task Orientation ($F_{(3,1231)}$=39.51, p<0.01), Student Cohesiveness ($F_{(3,1231)}$=12.85, p<0.00) and Organisation ($F_{(3,1231)}$=17.51, p<0.001). On the whole, as students progressed to higher grades, their perceptions of the English classroom learning environment became less positive. The mean and standard deviation for each ECLEI scale for each grade level are provided in Table 5.

Table 5. Mean and standard deviation for each ECLEI scale for four grade levels (N=1235)

Scale	Grade 7 (*n*=218)		Grade 8 (*n*=427)		Grade 10 (*n*=326)		Grade 11 (*n*=264)	
	M	SD	M	SD	M	SD	M	SD
Teacher Support	4.44	0.59	4.29	0.77	4.04	0.73	4.10	0.76
Task Orientation	4.19	0.60	3.88	0.72	3.62	0.75	3.56	0.78
Student Cohesiveness	3.83	0.91	3.49	0.81	3.81	0.73	3.69	0.80
Cooperation	3.95	0.74	3.90	0.79	3.97	0.69	3.94	0.79
Organisation	4.39	0.64	4.14	0.79	4.17	0.75	3.86	0.99

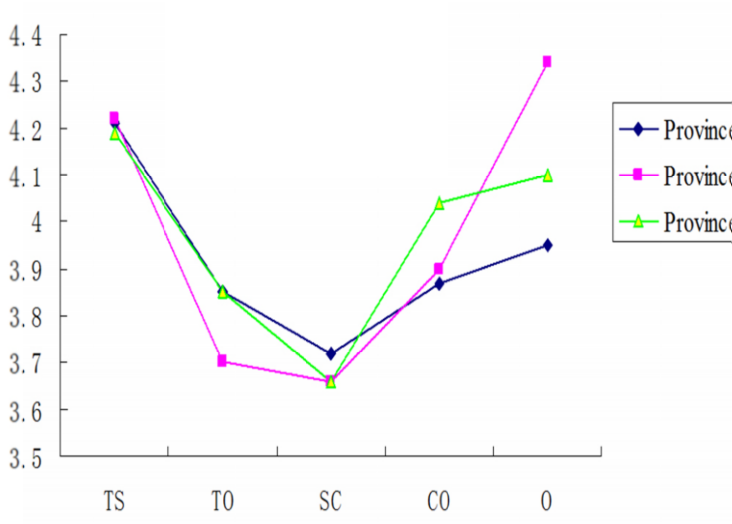

Figure 2. Students' perceptions of the English classroom learning environments in high schools from three provinces

Differences between Provinces in Students' Perceptions of the English Classroom Learning Environment

Analyses indicated that students from the three provinces in northeastern China held different perceptions of their English classroom learning environments. There were significant differences in students' perceptions of the three ECLEI scales of Task Orientation ($F_{(2,1232)}$=5.22, p<0.05), Cooperation ($F_{(2,1232)}$=5.81, p<0.05) and Organisation ($F_{(2,1232)}$=24.53, p<0.01). Generally speaking, students from Liaoning province (Province L) perceived Cooperation much more positively than the students from either Heilongjiang province (Province H) or Jilin province (Province J), but students from Jilin province perceived Organisation more positively than the students from the other two provinces. There was no clear difference between provinces for Teacher Support ($F_{(2,1232)}$=0.14, p=0.87). Figure 2 graphically depicts these between-province differences.

Associations between Students' Outcomes and Classroom Learning Environment

Associations between students' perceptions of the classroom learning environment and their English-related attitudes and academic achievement were investigated using structural equation modeling. As mentioned previously, an eight-item scale based on the Test of Science-Related Attitudes (Fraser, 1981), was used to measure students' attitudes to English. The sample consisted of 308 Grade 11 students.

With regard to the measurement of academic achievement, students' mid-year examination scores were used.

It was found that the Task Orientation, Student Cohesiveness, Cooperation and Organsiation scales had a positive impact on students' academic achievement. In particular, Task Orientation was positively and significantly related to achievement (β = 0.31, p < 0.05), whereas there was a negative, direct and significant association between Teacher Support and achievement (β = -0.33, p < 0.001). The results of structural equation modeling for achievement are shown in Figure 3.

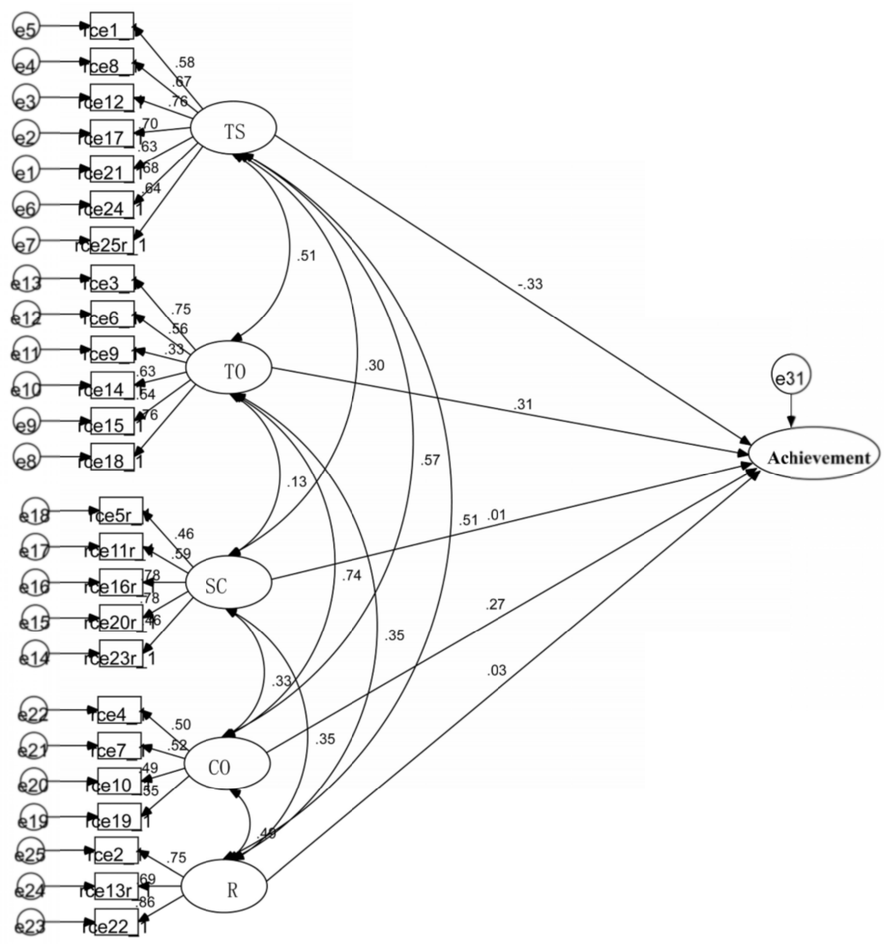

Figure 3. Associations between the English classroom learning environment and achievement (n = 308)

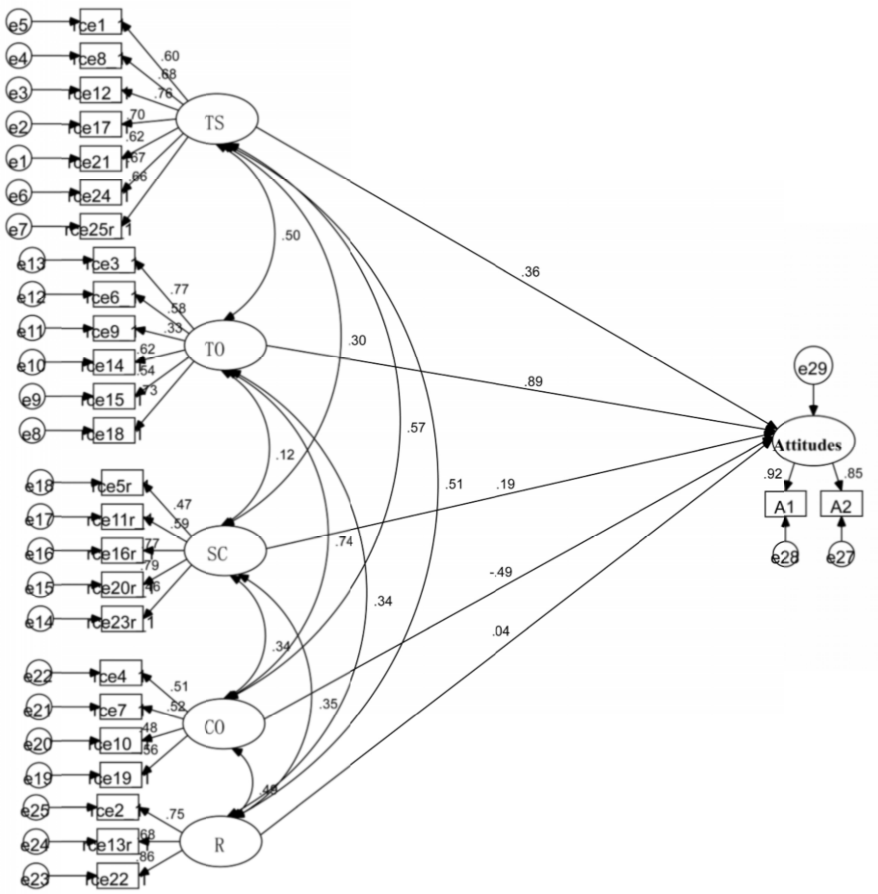

Figure 4. Associations between the English classroom learning environment and English-related attitudes (n = 308)

For the outcome of attitudes, Figure 4 shows the results from structural equation modeling are that Teacher Support, Task Orientation, Student Cohesiveness and Organisation had positive associations with students' English-related attitudes. The direct association between Task Orientation and attitudes was positive and significant (β = 0.89, p < 0.001), whereas Cooperation had a negative and significant impact on attitudes (β = -0.49, p < 0.01).

DISCUSSION AND CONCLUSIONS

This chapter has reported the development of an English classroom learning environment instrument and its application in Mainland China. According to

Moos' (1979) scheme, human environment scales can be classified into three general dimensions – relationship dimension, personal development dimension, and system maintenance and system change dimension. The final version of the ECLEI consists of 25 items in five scales that encompassed Moos' three general dimensions. Exploratory factor analysis and confirmatory factor analysis were carried out to confirm the validity of the instrument. Cronbach's alpha coefficient was used as a measure of internal consistency reliability. Overall, the study results supported the ECLEI's factorial validity and reliability for assessing students' perceptions of their English classroom in high schools in Mainland China.

Our research revealed sex differences in students' perceptions of their English classroom learning environment. By and large, female students tended to have more favourable perceptions of their classrooms environments than males, especially in areas of Cooperation and Student Cohesiveness, which is basically in line with past studies (Lim, 1995; Wong, Young, & Fraser, 1997). Our findings also agree with Levine and Donitsa-Schmidt's (1996) study of the classroom environment which showed that female students had more positive perceptions of the Affiliation dimension. The present study also supported Aldridge, Fraser and Huang's (1999) findings that Taiwanese high school girls perceived their classrooms more positively than boys.

Our study also revealed that junior high school students tended to have significantly more positive learning environment perceptions than senior high school students, especially for the Teacher Support and Student Cohesiveness dimensions. Interviews with some students in Grade 10 revealed that they received less help either from their teachers or their peers than they did when in junior high school, and that students felt that classroom activities became less interesting. This finding is in agreement with past studies that showed that students experienced less cooperation and less favourable relationships with teachers when they moved from elementary schools to junior high schools (Midgley, Eccles, & Fedlaufer, 1991). This result suggests that there was a gap between students' expectations and the actual classroom environment when students progressed to high school. Further research is needed to explore whether changes across the transition between levels of schooling are caused by differences in students' ages or by different teaching strategies or teacher–student interactions.

Our findings revealed differences in students' perceptions between provinces in the areas of Cooperation and Organisation. Students in Liaoning province generally perceived more Cooperation than students in the other two provinces. Students from Jilin province perceived higher levels of Organisation. The research question that is worth further exploring is whether these provincial differences are caused by the development of the economy or the distribution of the teaching resources and facilities.

It was found that some factors of the English classroom learning environment can significantly predict students' academic achievement and attitudes towards English. In particular, Task Orientation could predict students' achievement and attitudes towards English and attitudes towards English was a mediator between students' perceptions of English classroom environment and their academic achievement. The present study provided evidence to support the assertion that students' perceptions of classroom learning environment affect their achievement and attitudes, which is consistent with considerable prior research (Fraser, 2012).

It is interesting to note that Teacher Support was negatively related to students' academic achievement, which is inconsistent with most previous studies with the exception of one study that revealed the teacher support had a negative impact on academic results in Chinese, English and Mathematics (Lee, Lee, & Wong, 2003).

Cooperation had a negative association with students' English-related attitudes in our study. Through interviews, some teachers revealed that they believed that independent learning was very important for senior high school students; the more support that teachers offer, the more that students would rely on them. However, if some students don't know how to study independently, this would negatively influence students' achievement. Through classroom observation, researchers found cooperation was often promoted through group work in the English class; but the results of group work generally were reported by only one dominant student in a group, while the other members of the group normally kept silent and depended on the active group member. Offering appropriate support to students, enhancing teacher support based on improving teachers' professional knowledge, and organising classroom group work activities to promote cooperation effectively are some practical recommendations that flow from our research.

Our study is pioneering in that it involved developing a questionnaire to assess students' perceptions of their English classroom learning environment in high schools in China and exploring associations between the English classroom learning environment and student achievement and attitudes. Few past studies have investigated these questions in China. Another practical contribution made by the present study is that English teachers can use the newly-developed classroom environment instrument to assess students' perceptions of their classroom learning environment to guide improvements in their classroom environments using approaches described by Aldridge, Fraser, Bell and Dorman (2012).

Finally, our research is one of a relatively small number of studies that has used structural equation modeling in investigating associations between the nature of the classroom environment and student learning outcomes.

APPENDIX A

English Classroom Learning Environment Inventory (ECLEI)

Directions

This questionnaire contains statements that could take place in your English class. It describes how often each practice happens in your English class. Please give an answer for each question. There is no right or wrong answer. Your opinions are welcome. Your responses will be confidential.

Draw a circle around:

1 if the practice **Almost Never** takes place

2 if the practice **Seldom** takes place
3 if the practice takes place **Sometimes**
4 if the practice takes place **Often**
5 if the practice takes place **Almost Always**

My English Class

	Almost Never	Seldom	Sometimes	Often	Almost Always
1. Our English teacher likes us.	1	2	3	4	5
2. Our English class is very orderly.	1	2	3	4	5
3. I pay attention during English classes.	1	2	3	4	5
4. Most students co-operate equally with other class members.	1	2	3	4	5
5. Students in my class like to fight.	1	2	3	4	5
6. I am ready to start this class on time.	1	2	3	4	5
7. I work with other students in this class.	1	2	3	4	5
8. Our English teacher is good at teaching.	1	2	3	4	5
9. I know what I should accomplish in this class.	1	2	3	4	5
10. Most students co-operate rather than compete with one another.	1	2	3	4	5
11. Certain students don’t like to get on well with others.	1	2	3	4	5
12. Our English teacher is our friend.	1	2	3	4	5
13. Our English Class is disorganized.	1	2	3	4	5
14. I know the goal for this class.	1	2	3	4	5
15. I can finish my English homework on time.	1	2	3	4	5
16. Some students don’t like others in my class.	1	2	3	4	5

17. Our English teacher pays attention to our questions.	1	2	3	4	5
18. I will try to accomplish the assignments in English class.	1	2	3	4	5
19. I share my books and resources with other students when doing English assignments.	1	2	3	4	5
20. Certain students in my class are mean.	1	2	3	4	5
21. Our English teacher encourages us to raise questions in class.	1	2	3	4	5
22. Our English class is well organized.	1	2	3	4	5
23. Certain students work only with close friends.	1	2	3	4	5
24. Our English teacher will accept our opinions.	1	2	3	4	5
25. Our English teacher rarely talks with us.	1	2	3	4	5

Refer to Table 1 to identify which of the 25 items belong to each of the five ESCLEI scales.

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5. THE EFFECTS OF PSYCHOSOCIAL LEARNING ENVIRONMENT ON STUDENTS' ATTITUDES TOWARDS MATHEMATICS

BACKGROUND

Learning Environments

Students spend up to 20,000 hours at educational institutions by the time they finish university (Fraser, 2001). Therefore, students' observations of and reactions to, their experiences in school – specifically their learning environments – are of significance. The term learning environment refers to the social, physical, psychological and pedagogical context in which learning occurs and which affects student achievement and attitudes (Fraser, 2007, 2012).

The notion of a learning environment existed as early as 1936 when Lewin proposed that both the environment and its interaction with personal characteristics of the individual are potent determinants of human behaviour. To this end, he developed the formula B = f (P, E) in which behaviour (B) is a result of the interaction between the person (P) and environmental factors (E). Murray (1938) identified that Lewin's formula did not take into account the personal needs of an individual. To address this shortcoming he proposed a needs-press model in which an individual's behaviour is affected internally by characteristics of personality (needs) and externally by the environment itself (press). Personal needs refers to motivational personality characteristics representing tendencies to move in the direction of certain goals, while environmental press provides an external situational counterpart which supports or frustrates the expression of internalised personality needs.

Results of studies conducted over the past 40 years have provided convincing evidence that the quality of the classroom environment in schools is a significant determinant of student learning (Fraser, 2007, 2012). That is, students are likely to learn better when they perceive their classroom environment positively (Dorman & Fraser, 2009; Velayutham & Aldridge, 2012). Many of these studies have controlled for background variables with students' perceptions of the classroom environment accounting for appreciable amounts of variance in learning outcomes, often beyond that attributable to background student characteristics (Dorman & Fraser, 2009).

Recent studies have substantiated this position. For example, using a modified What Is Happening In this Class? (WIHIC), Opolot-Okurut (2010) established associations between students' perceptions of their mathematics classroom

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 91–114.

learning environment and motivation among a sample of 81 secondary school students in two schools in Uganda, Africa. Kerr, Fisher, Yaxley and Fraser (2006) established positive relationships between classroom environment and attitudinal outcomes in Australian science classes. Associations with students' cognitive and affective outcomes have been established, using the Science Laboratory Environment Inventory (SLEI), for a sample of approximately 80 senior high-school chemistry classes in Australia (Fraser & McRobbie, 1995), 489 senior high-school biology students in Australia (Fisher, Henderson & Fraser, 1997) and 1,592 grade 10 chemistry students in Singapore (Wong & Fraser, 1996).

In California, USA, Ogbuehi and Fraser (2007) found associations between perceptions of classroom learning environment and students' attitudes to mathematics and conceptual development among a sample of 661 middle-school students in 22 classes using modified versions of the What Is Happening In this Class? (WIHIC), Constructivist Learning Environment Survey (CLES) and Test of Mathematics Related Attitudes (TOMRA).

In Singapore, Teh and Fraser (1995) established associations between classroom environment, achievement and attitudes among a sample of 671 high-school geography students in 24 classes using an instrument suited for computer-assisted instruction classrooms. Fisher, Henderson and Fraser (1995) used the Questionnaire on Teacher Interaction (QTI) to establish associations between student outcomes and perceived patterns of teacher-student interaction for samples of 489 senior high-school biology students in Australia.

Wong, Young and Fraser (1997) investigated associations between three student attitude measures and a modified version of the SLEI involving 1,592 grade 10 students in 56 chemistry classes in Singapore. In India, Koul and Fisher (2006) found positive associations between scales of the What Is Happening In this Class? (WIHIC) questionnaire and students' attitude towards science. Similarly, Telli, Cakiroglu and den Brok (2006) found positive associations between scales of the WIHIC and students' attitude to biology in Turkish high schools. Telli, den Brok and Cakiroglu (2010) investigated the associations between teacher-student interpersonal behaviour and students' attitudes to science using the QTI with an attitude questionnaire for a sample of 7,484 grade 9-11 students from 278 classes in 55 public schools in 13 major Turkish cities. Their results revealed that the influence dimension of the QTI was related to student enjoyment, whilst the proximity dimension was associated with attitudes to inquiry.

Kyriakides (2006) administered the QTI (Wubbels & Levy, 1993) to elementary school students in Cyprus and established positive links between teacher interaction and affective outcomes. Other environment-outcomes studies have investigated school-level environments and student outcomes in mathematics (Webster & Fisher, 2004), the relationship between learning environments, family contexts, educational aspirations and attainment (Marjoribanks, 2004). Some researchers have also investigated the relationship between learning environment, attitudes and achievement in middle schooling science classes (Wolf & Fraser, 2008); mathematics classroom environment and academic efficacy (Dorman, 2001); and school and classroom environment and teacher burnout (Dorman, 2003a).

Confirmatory factor analysis and structural equation modeling have been employed in recent learning environments studies. Dorman (2003b) employed LISREL to establish the factorial invariance of the WIHIC according to country, gender and year of student. Den Brok, Fisher, Wubbels, Brekelmans and Rickards (2006) performed multigroup confirmatory factor analysis on Questionnaire on Teacher Interaction (QTI) data collected in Singapore, Brunei and Australia. Aldridge, Dorman and Fraser (2004) used multitrait-multimethod modeling to validate actual and preferred forms of the Technology-Rich Outcomes-Focused Learning Environment Inventory (TROFLEI). Their results provided strong evidence of the sound psychometric properties of the TROFLEI. Structural equation modeling and multilevel modeling have advanced the data analysis techniques employed in the field of learning environments (see: den Brok, Brekelmans, & Wubbels, 2006; den Brok, Fisher, Rickards, & Bull, 2006; Dorman, Fisher, & Waldrip, 2006; Dorman & Fraser, 2009; Fisher, Waldrip, & den Brok, 2005; Velayutham & Aldridge, 2012).

Dorman and Fraser (2009) used structural equation modeling to develop a comprehensive model representing the relationships among classroom environment, its antecedents and outcomes. In a more recent study, Velayutham and Aldridge (2012) used structural equation modeling to investigate the influence of psychosocial aspects of classroom environment on students' motivation and self-regulation in the area of science learning. Their results suggested that student cohesiveness, investigation and task orientation were the most influential predictors of student motivation and self-regulation in science learning.

In another recent study, Velayutham, Aldridge and Fraser (2012) used multi-group structural equation modeling analysis to examine gender differences in student motivation and self-regulation in science learning. Their study revealed that the influence of task value on self-regulation was statistically significant for boys only.

My study investigated the effects psychosocial features of the classroom environment (Teacher Support, Involvement and Personal Relevance) on students' enjoyment of mathematics lessons and academic self-efficacy in mathematics learning in the United Arab Emirates, using structural equation modeling.

Students' Attitudes

The conceptions, attitudes and expectations of students regarding mathematics and mathematics teaching are considered to be significant factors underlying their school experience and achievement (Borasi, 1990; Reed, Drijvers, & Kirschner, 2010). In reviewing the issue of students' attitudes towards mathematics, Westwood (2000, p. 31) cites the work of Wain who painted a rather dark image of mathematics:

> Many intelligent people after 1500 hours of instruction over eleven years of schooling still regard mathematics as a meaningless activity for which they have no aptitude. It is difficult to imagine how a subject could have achieved for itself such an appalling image as it now has in the popular mind to think that all our effort has led to a situation of fear.

While this picture of mathematics is not a pleasant one, it represents a 'wake-up call' for all of those involved in the teaching of mathematics (Swan, 2004). Davis (1993, p. 1) goes further when he states that:

> Some students seem naturally enthusiastic about learning, but many need-or-expect their instructors to inspire, challenge, and stimulate them. Whatever level of motivation your students bring to the classroom, will be transformed, for better or worse, by what happens in that classroom.

Learning clearly has an affective component and, according to Kind, Jones and Barmby (2007), developing a positive attitude is important for students' achievement. One definition that is commonly used to describe attitudes includes the three components of cognition, affect and behaviour (Kind et al., 2007; Rajecki, 1990). These three components are defined by Reid (2006, p. 4) as "a knowledge about the object, or the beliefs and ideas component (cognitive); a feeling about the object, or the like or dislike component (affective); and a tendency towards action, or the objective component (behavioural)".

As Kind et al. (2007) point out, this definition is a sensible view of attitudes because these components are closely linked. For example, we know about mathematics (cognitive) and therefore we have a feeling or an opinion about it (affective) that may cause us to take a particular action (behavioural). Other researchers have suggested that the three components should be treated more independently, and that attitudes should be viewed as basis for evaluative judgements (Ajzen, 2001; Crano & Prislin, 2006). According to Kind et al. (2007) when we have an attitude, we judge something along emotional dimensions, such as good or bad, harmful or beneficial, pleasant or unpleasant, important or unimportant. Crano and Prislin (2006) point out that it is important to notice that these evaluative judgements are always towards something, often called the attitude object. Although some researchers have defined attitudes solely in terms of the affective component (George, 2000; Germann, 1988), Fishbein and Ajzen (1975) viewed attitudes as being formed spontaneously and, inevitably, involving the attributes of an object. Attitudes or the affective component of attitudes, therefore, are linked to the beliefs that a person holds (Kind et al., 2007). It is with this in mind that the definition for attitude, used for my study, is the feelings that a person has about an object, based on their beliefs about that object.

When children start school, their attitude towards learning is derived primarily from their home environment (Lumsden, 1994). However, success or failure in the classroom impacts on these initial attitudes and is shaped by early school experiences which, in turn, impact on subsequent classroom situations (Lumsden, 1994; Reynolds & Walberg, 1992). In addition, students' attitudes are affected by their interactions with their peers (Fishbein & Ajzen, 1975; Reynolds & Walberg, 1992; Taylor, 1992). Positive and negative experiences of school activities produce learned responses which may then impact on students' attitudes as they get older (Dossey, Mullis, Lindquist, & Chambers, 1988).

Students' attitudes towards mathematics influence the extent to which learning outcomes are realised (Reed et al., 2010). One aspect of my study involved determining the effects of teacher support, involvement and personal relevance on students' attitudes towards mathematics, in particular, their enjoyment of mathematics lessons and academic self-efficacy.

Academic Self-efficacy

More than three decades ago, Bandura (1977) theorised that a potent influence on student behaviour is the beliefs that they hold about their capabilities. According to social cognitive theory, students are more likely to have an incentive to learn if they believe that they can produce the desired outcomes (Bandura, 1986). Hence, self-efficacy beliefs are powerful predictors of the choices that students make, the effort that they expend and their persistence in facing difficulties. Furthermore, aside from task value, a major motivational component of expectancy-value theory is ones self-efficacy beliefs. In their expectancy-value theory, Eccles and Wigfield (2002) envisage the direct influence of students' expectation beliefs on both achievement-related choices and performance. Furthermore, according to Pajares (2002), self-efficacy is intimately related to students' self-regulated learning. Students with high efficacy are more likely to put in more effort, consistently evaluate their progress and apply self-regulatory strategies (Schunk & Pajares, 2005).

Velayutham, Aldridge and Fraser (2011) examined the influence of motivational constructs (learning goal orientation, task value and self-efficacy) in science learning on students' self-regulation in science classrooms involving 1360 science students in grades 8, 9 and 10 in Perth, Australia. Their results revealed that motivational beliefs of learning goal orientation, task value and self-efficacy significantly influenced students' self-regulation in science learning.

Previous research has established that self-efficacy is a predictor of academic achievement (Bandura, 1997; Edman & Brazil, 2007; Gore, 2006; Hsieh, Sullivan, & Guerra, 2007; Tyler & Boelter, 2008) and influences academic motivation and learning (Adeyemo, 2007; Pajares, 1996). Researchers have demonstrated that self-efficacy beliefs predict students' mathematics performances (Bandura, 1986; Pajares, 1996; Schunk, 1991). Interestingly, Pajares and Kranzler (1995) found that the influence of self-efficacy on mathematics performance was as strong as was the influence of general mental ability.

About 13 years ago, Lorsbach and Jinks (1999) brought to the attention of learning environment researchers, the influence of classroom environment on academic efficacy. According to Lorsbach and Jinks (1999), student self-efficacy beliefs regarding academic performance can have important implications for improving learning environments and student outcomes. Additionally, focusing on students' academic self-efficacy could alter student perceptions of the learning environment. Dorman (2001) and Dorman and Adams (2004) took up this challenge and established the relationship between students' academic efficacy and classroom environment. Using simple and multiple correlation analyses, their results indicate that the mathematics classroom environment is positively related to student academic efficacy.

A study of classroom environment, perceptions of assessment tasks, academic efficacy and attitude to science revealed significant links between classroom environment and academic efficacy (Dorman & Fraser, 2009). A more recent study of Velayutham and Aldridge (2012) identified aspects of the psychosocial learning environment that influence student motivation (including self-efficacy). Their results suggested that the student cohesiveness, task orientation and investigation were the most influential predictors of student self-efficacy.

One premise of my study was that student self-efficacy beliefs regarding competence could have important implications for improving learning environments and therefore, student outcomes (Aldridge & Fraser, 2008; Lorsbach & Jinks, 1999, Velayutham & Aldridge, 2012). Hence my study aimed to investigate whether associations exist between students' enjoyment and self-efficacy and their perceptions of the learning environment.

AIMS OF THE STUDY

The study described in this chapter was carried out to investigate whether three psychosocial features of the classroom environment (teacher support, involvement and personal relevance) can influence students' enjoyment of mathematics lessons and academic self-efficacy in mathematics learning in the United Arab Emirates, using structural equation modeling.

METHOD

Participants

The participants for this study were 352 first and second year mathematics students attending three colleges in the United Arab Emirates. Among the participants, 231 (66%) were female and 121 (34%) were male. The participants' age ranges from 18 to 35 years. About 90% of the students were United Arab Emirates nationals and the rest were from the neighbouring Arab countries. The questionnaire was administered at the middle of the semester. Participants completed the questionnaires in their classrooms during normal school hours. I distributed the questionnaire, explained the procedure, and answered students' clarifications. The students took approximately 20 minutes to complete the questionnaires and participation was voluntary.

Variables in the Model

I adapted the Teacher Support scale, consisting of eight items, from a widely used learning environment instrument: The What is Happening in This Classroom (WIHIC; Aldridge, Fraser, & Huang, 1999). The Teacher Support scale assesses the extent to which the teacher helps, relates to, trusts and is interested in students. The teacher's relationship with his or her students is an important aspect of any learning environment, and it can lead the student to love or hate a subject, and to be inspired or turned away from learning. The supportiveness of a teacher helps to give students the courage and confidence needed to tackle new problems, take risks in their learning, and work on and complete challenging tasks. If students consider a teacher to be approachable and interested in them, then they are more likely to seek the teacher's help if there is a problem with their work. The teacher's relationship with his or her students, in many ways, is integral to a student's success and to creating a cooperative learning environment (Hijzen, Boekaerts, & Vedder, 2007). The response format involves a five-point frequency scale consisting Almost Always, Often, Sometimes, Seldom and Almost Never. A typical item is "The teacher helps me when I have trouble with the work". In my study, the internal consistency (Cronbach's alpha) of the Teacher Support scale was 0.89 and considered an internally reliable scale.

The Involvement scale assesses the extent to which students feel that they have opportunities to participate in discussions and have attentive interest in what is happening in the classroom. The Involvement scale assumes that language plays an important part in helping students to understand what they are learning (Taylor & Campbell-Williams, 1993) and that giving students the opportunity to participate in classroom discussions and to negotiate ideas and understandings with peers, rather than listening passively, is an important aspect of the learning process. The response format involves a five-point frequency scale consisting Almost Always, Often, Sometimes, Seldom and Almost Never. Typical item is "I explain my ideas to other students". In my study, the internal consistency (Cronbach's alpha) of the Involvement scale was 0.87 and considered an internally reliable scale.

The Personal Relevance scale, consisting of eight items, was adapted from the Constructivist Learning Environment Survey (CLES; Taylor, Fraser and Fisher 1997). To ensure that students engage in their learning, it is necessary for teachers to make mathematical content relevant to students' lives outside school (Nicol, 2002; Taylor et al., 1997). The Personal Relevance scale assesses the connectedness of a subject with students' out-of-school experiences. The response format involves a five-point frequency scale consisting Almost Always, Often, Sometimes, Seldom and Almost Never. Typical item is "This class is relevant to my life outside college". In my study, the internal consistency (Cronbach's alpha) of the Personal Relevance scale was 0.89 and considered an internally reliable scale.

The eight-item Academic self-efficacy scale was based on Jinks and Morgan (1999) Student Efficacy Scale (MJSES). The Academic self-efficacy scale assesses the extent to which students have confidence in their academic competence. A student's self-efficacy positively affects engagement and effort and is important to learning (Aldridge & Fraser, 2008; Bandura, 1989; Velayutham, Aldridge, & Fraser, 2011; Zimmerman, Bandura, & Martinez-Pons, 1992). The response alternatives for each item are Almost Always, Often, Sometimes, Seldom and Almost Never. Examples of items are "I find it easy to get good grades in mathematics" and "I feel that I am an intelligent student". In my study, the Cronbach alpha reliability for the academic self-efficacy scale was 0.93 and considered an internally reliable scale.

The Enjoyment of Mathematics Lessons scale, consisting of eight items, was adapted from one scale in the Test of Science-Related Attitudes (TOSRA; Fraser, 1981) by Spinner and Fraser (2005). The Enjoyment of Mathematics Lessons scale assesses the extent to which students enjoy their mathematics lessons. The response alternatives for each item are Almost Always, Often, Sometimes, Seldom and Almost Never. Examples of items are "Lessons in mathematics are fun" and "I enjoy the activities that we do in mathematics". In my study, the Cronbach alpha reliability for the enjoyment of mathematics lessons scale was 0.95 and considered an internally reliable scale. My results for the sound internal consistency reliability of the three learning environment scales (teacher support, involvement and personal relevance) and the two attitude scales (enjoyment of lessons and academic self-efficacy), when used with college students in the United Arab Emirates, replicates past research (Afari, Aldridge, Fraser, & Khine, 2013; Aldridge & Fraser, 2008; Fraser, Aldridge, & Adolphe, 2010; MacLeod & Fraser, 2010). Table 1 provides a scale description and sample item for each of the scales used in my study.

Table 1. Scale description and sample item for each of the questionnaire used in the study

Scale	Description	Sample Item
Learning Environment	*The extent to which …*	
Teacher Support	the teacher helps, befriends and is interested in students.	The teacher helps me when I have trouble with the work.
Involvement	students have attentive interest, participate in discussions and enjoy the class.	I explain my ideas to other students.
Personal Relevance	there is a link between what is taught and students' out of school experiences.	This class is relevant to my life outside college.
Attitudes		
Enjoyment of Mathematics Lessons	students enjoy their mathematics lessons.	Lessons in mathematics are fun.
Academic Self-Efficacy	students have confidence in their academic competence.	I find it easy to get good grades in mathematics.

Note: All items used the response alternatives of Almost Always, Often, Sometimes, Seldom and Almost Never.

Model and Analysis

Researchers now have many sophisticated methodological tools to analyse nonexperimental data. Structural equation modeling or path analysis is an especially appropriate method for analysis of causal relations in nonexperimental data (Cohen & Cohen, 1983; Keith, 1993). In path analysis, the researcher develops a model of hypothesized causes and effects based on previous research and theory. Latent variable structural equation modeling is different from ordinary path analysis in that it uses measured variables (generally multiple indicators) to infer latent variables (Singh, 1998). Latent variables equate to "factors" in factor analytic techniques (Arbuckle & Wothke, 1999; Byrne, 2010; Joreskog, 1977; Kline, 2010; Ullman, 2001). Latent variable structural equation modeling carries out confirmatory factor analysis and path analysis of the latent factors simultaneously.

Structural equation models are either recursive or nonrecursive. Recursive models have unidirectional "causal" relationships (Arbuckle & Wothke, 1999; Byrne, 2010; Kline, 2010; Ullman, 2001) and an independent error terms (Kline, 2010; Ullman, 2001). Nonrecursive models have bidirectional "causal" relationships, that is, feedback loops (Arbuckle & Wothke, 1999; Byrne, 2010; Kline, 2010; Ullman, 2001) correlated error terms, or both (Kline, 2010; Ullman, 2001).

One advantage of latent variable models is that unobserved latent variables are relatively free of measurement error and closely approximate the constructs of interest. Another advantage of the method is that fit indices provided in the output assess the adequacy of the model in explaining the data. These features make structural equation modeling a rigorous method for estimating cause-effect relationships in nonexperimental data.

I developed the initial model for my study on the basis of previous research and theory, which is presented in Figure 1. The research model hypothesizes that each of the three psychosocial aspects of the learning environment (teacher support, involvement and personal relevance) would influence each of the two attitude constructs (enjoyment of mathematics lessons and academic self-efficacy). Additionally, academic self-efficacy is predicted to influence enjoyment of mathematics lessons.

First, the measurement part of the model (construct and their indicators) was specified and estimated, and then structural relationships in the model were specified and estimated. I fully specified the factor pattern and specified the relations among latent variables to arrive at a latent-variable structural equation modeling. Latent variable structural equation modeling (SEM) makes it possible to estimate and test the measurement and structural parts of the model simultaneously. Although cause-effect relationships can be ascertained with any certainty only in experimental research, in nonexperimental research the estimation of cause-effect relationships is best done with structural equation modeling (SEM). SEM is an especially appropriate method for analyzing nonexperimental data and for bringing empirical support for an a priori and theoretically sound model (Cohen & Cohen, 1983; Keith, 1993, Singh, Granville, & Dika, 2002).

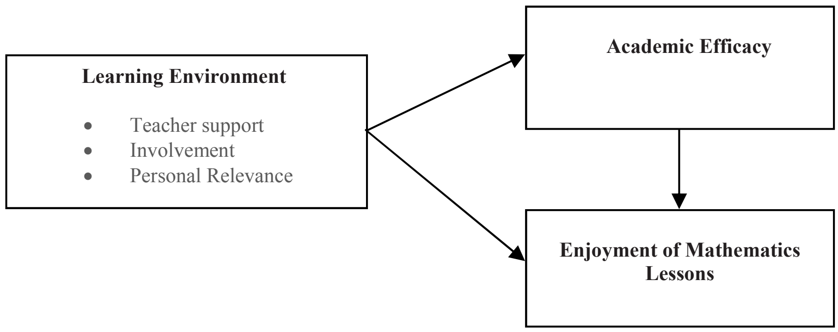

Figure 1. Hypothesized structural model of the study

Data was analyzed by means of confirmatory factor analysis and structural equation modeling (SEM), with maximum likelihood estimation, using Analysis of Moment Structure (AMOS) version 18 software program (Arbuckle & Wothke, 1999). In this approach a hypothesized model of relations between variables is tested statistically to determine the extent to which it is consistent with the data, which is referred to as the goodness of fit. If the goodness of fit is adequate it supports the plausibility of the relations among variables (Skaalvik & Skaalvik, 2010).

AMOS provides a number of relevant statistics, including a chi-square statistics (χ^2) that can be used to test whether the empirical data sufficiently fit a proposed theoretical model. It has generally been accepted that χ^2 should be expressed relative to the corresponding degrees of freedom (d.f.) for the model (Joreskog & Sorbom, 1993; Meeuwisse, Severiens, & Born, 2010). A small χ^2 value relative to its degree of freedom is indicative of good fit (Hoe, 2008). Kline (2010) suggested that χ^2 /*d. f.* ratio of 3 or less is a reasonably good indicator of model fit.

There are many indices for measuring how well a model fits the data. I used four indicators of fit to assess the models tested, including the chi-square goodness-of-fit test (Jöreskog, 1977), the Comparative Fit Index (CFI; Bentler, 1990), the Incremental Fit Index (IFI; Bollen, 1989) and the root mean square error of approximation (RMSEA; Brown & Cudeck, 1993). For the CFI and IFI indices, values greater than 0.90 are typically considered acceptable and values greater than 0.95 indicate a good fit to the data (Bollen, 1989; Byrne, 2010; Hu & Bentler, 1999). For well specified models, an RMSEA of less than 0.05 is considered to have a good model fit, values up to 0.08 reasonable fit and ones between 0.08 and 0.10 indicate mediocre fit (Hoe, 2008; Hu & Bentler, 1999).

RESULTS

First, I examined the descriptive statistics of the measurement items and assessed the reliability and validity of the measures used in the study. This was followed by testing for model fit and assessing the contributions and statistical significance of the manifest variables' path coefficients.

Descriptive Statistics

The descriptive statistics of the 5 constructs (teacher support, involvement, personal relevance, enjoyment of mathematics lessons and academic self-efficacy) are shown in Table 2. All means were greater than 3.0, ranging from 3.58 to 4.02. This indicates an overall positive response to the constructs that are measured in this study. The standard deviations for all the variables were less than one, ranging from 0.73 to 0.99, indicating that the item scores were relatively close to the mean scores. The skewness ranged from -0.34 to -0.77 and kurtosis ranged from -0.27 to 0.12. Following Kline's (2010) recommendations that the skew and kurtosis indices should be below an absolute value of 3.0 and 8.0, respectively, the data in this study was regarded as normal for the purpose of structural equation modeling.

Table 2. Descriptive statistics of teacher support, personal relevance, enjoyment of mathematics lessons and academic self-efficacy

Construct	Mean	Standard deviation	Skewness	Kurtosis
Teacher Support	4.02	0.79	-0.77	0.12
Involvement	3.66	0.73	-0.34	-0.47
Personal Relevance	3.58	0.83	-0.44	-0.43
Enjoyment of Mathematics Lessons	3.61	0.99	-0.56	-0.61
Academic Efficacy	3.76	0.91	-0.65	-0.27

Convergent Validity

Fornell and Larcker (1981) proposed three procedures to assess for convergent validity of the measurement items in relation to their corresponding constructs. These are (1) item reliability of each measure, (2) composite reliability of each construct, and (3) the average variance extracted. The item reliability of an item was assessed by its factor loading onto the underlying construct. Hair, Black, Babin, Anderson (2010) suggested that an item is significant if its factor loading is greater than 0.50. Table 3 shows that the factor loadings of all the items in the measure ranged from 0.536 (item PR2) to 0.918 (item EOM6). In this study, the composite reliability was used instead of the cronbach's alpha because the latter tends to understate reliability (Hair, et al., 2010). For the composite reliability to be adequate, a value of 0.70 or higher was recommended (Nunnally & Bernstein, 1994). The results (Table 3) show that all five constructs met the suggested

Table 3 Item loading, composite variance and average variance extracted

Latent Variable	Item	Factor loading	Average Variance extracted (>0.50)*	Composite reliability (>0.70)*
	TS8	0.680		
	TS7	0.669		
	TS6	0.829		
Teacher Support	TS5	0.775	0.516	0.894
	TS4	0.727		
	TS3	0.717		
	TS2	0.650		
	TS1	0.681		
	INV8	0.718		
	INV7	0.708		
	INV6	0.713		
Involvement	INV5	0.691	0.514	0.894
	INV4	0.721		
	INV3	0.721		
	INV2	0.697		
	INV1	0.768		
	PR8	0.614		
	PR7	0.729		
	PR6	0.788		
Personal Relevance	PR5	0.784	0.519	0.895
	PR4	0.788		
	PR3	0.786		
	PR2	0.536		
	PR1	0.692		
	AE8	0.744		
	AE7	0.601		
	AE6	0.822		
Academic Efficacy	AE5	0.786		
	AE4	0.874	0.631	0.926
	AE3	0.813		
	AE2	0.876		
	AE1	0.807		
	EOM8	0.884		
	EOM7	0.861		
	EOM6	0.918		
Enjoyment	EOM5	0.657	0.698	0.948
	EOM4	0.868		
	EOM3	0.811		
	EOM2	0.825		
	EOM1	0.836		

[*]Indicates an acceptable level of reliability or validity.
Note: CR is computed by $(\sum\lambda)^2 / (\sum\lambda)^2 + \sum(1-\lambda^2)$*; AVE is computed by* $\sum\lambda^2 / \sum\lambda^2 + \sum(1-\lambda^2)$

minimum value of 0.70. The final criterion to satisfy convergent validity was the measure of the average variance extracted (AVE). AVE is a measure that indicates the amount of variance in the item that is explained by the construct. The results of the statistical analysis (Table 3) show that all of the AVE values were above the suggested value of 0.5.

Therefore, the measurement model satisfied all three necessary criteria and achieved convergent validity. Hence the results indicated that the items in each construct were highly correlated and reliable.

Discriminant Validity

Discriminant validity assesses the degree to which the constructs differ from each other. As suggested by Barclay, Higgins and Thompson (1995), I assessed the discriminant validity by applying two analytical procedures. The first criterion of discriminant validity was that the square root of average variance extracted (AVE) for each construct is larger than the inter-construct correlation. The data analysis results (Table 4) support the discriminant validity because for each construct, the square root of the AVE is larger than inter-construct correlation. As stipulated by Gefen, Straub and Boudreau (2000), the second discriminant validity criterion is achieved when the loading of an item within a construct is greater than its loading in any other construct in the model. My results of cross-loading correlations show that all items loaded higher in the construct that they are measuring than on any other construct in the model. Therefore, the second criterion of the discriminant validity was met. The two analyses confirmed that the individual constructs are discriminated from each other by the instrument.

Table 4. Inter-construct correlations and square roots of average variance extracted

Construct	TS	PR	INV	EOM	AE
Teacher Support (TS)	**0.718**				
Personal Relevance (PR)	0.185**	**0.720**			
Involvement (INV)	0.304**	0.242**	**0.717**		
Enjoyment of Mathematics Lesson (EOM)	0.237**	0.303**	0.305**	**0.835**	
Academic Efficacy (AE)	0.117*	0.208**	0.136**	0.479**	**0.794**

**p< 0.05; **p< 0.01*
Note: The bold elements in the main diagonal are the square roots of average variance extracted

Model Fit

The examination of the fit indices is the first step in model evaluation because the fit statistics help determine the adequacy of the model in explaining the data. The fit indices compare the residual differences between the covariance matrix implied by the model and the actual covariance matrix used to analyze the data (Singh & Billingsley, 1998).

Using structural equation modeling (SEM) procedure with AMOS 18, I tested the model in Figure 1 specifying three correlated latent variable; a second order teacher support, involvement and personal relevance and also an academic efficacy and enjoyment of mathematics lessons. AMOS generates a chi-square (χ^2) statistics, associated degree of freedom (df) and a probability value whenever maximum-likelihood estimates are computed. In addition, AMOS uses Hoelter's formula for critical N (CN) to estimate a sample size that would be sufficient to yield an adequate model fit for χ^2 test (Hu & Bentler, 1995). Both the .05 and .01CN values for my hypothesized model were 202 and 209, respectively. The sample size for this SEM analysis is 352.

The primary fit index is the chi-square value; for this model, χ^2 (249, N = 352) =766.04, p<0.001. The significant value of the chi-square indicates a significant difference between the input covariance matrix and covariance matrix implied by the model and, thus suggesting that the fit of the data to the hypothesized model is not entirely adequate. Although a significant chi-square value for the model suggest a poor fit, it is important to examine the other fit indices. The fit indices for the initial model are given in Table 5, from which it can be seen that this model did not fit the data well (χ^2 = 1856.49, CFI = 0.90, IFI = 0.90, RMSEA = 0.07).

Table 5. Summary of fit indices

Index	χ^2	df	CFI	IFI	RMSEA
Initial model	*1856.49*	730	0.90	0.90	0.07
Final Model	1372.34	724	0.93	0.93	0.05

Note: CFI = comparative index; IFI = incremental fit index; RMSEA = root-mean-square of error of approximation.

In addition to the fit statistics, AMOS also provides the standardized and unstandardized loadings with standard errors, critical ratio, and modification indices to assess which aspects of the model are misspecified and, thus, can be modified.

Examination of the modification indices suggests that estimation of some correlated errors would improve the fit of the model. The correlated errors indicated that some of these items shared specific variance that was not part of the latent variable. Although modification indices pointed to the source of the misspecification, I attended to only those modifications which were theoretically defensible; namely, the inclusion of six error covariance (namely, items PR5 and PR6 of the personal relevance scale, items EOM1 and EOM2 and items EOM3 and EOM4, both are items of the enjoyment of mathematics lessons scale, items AE3 and AE8 of the academic self-efficacy scale, and both items INV7 and INV8 and items INV1 and INV2 of the involvement scales). Items EOM1 and EOM2, and

Items EOM3 and EOM4 suggest redundancy due to content overlap. Item EOM1 asks if respondent looks forward to lessons in mathematics, whereas item EOM2 asks if respondent feels lessons in mathematics are fun. Clearly, there appears to be an overlap of content between these items. Similarly Item EOM3 asks respondent if mathematics is one of their favourite school subjects, whereas item EOM4 asks respondent if lessons in mathematics interest them. Again, there appears to be an overlap of content between these items.

Also, Item INV1 asks if respondent discusses ideas in class, whereas Item INV2 asks if respondent gives his or her opinions during class discussions. There appears to be a clear overlap of content. Finally, both Items AE3 and AE8 also suggest redundancy due to content overlap. Item AE3 asks respondent if their friends ask them for help in mathematics, whereas item AE8 asks if respondent helps their friends with their homework in mathematics. Clearly, there appears to be an overlap of content between these items. These error covariances are explicable in relation to content.

Table 6 reports the path coefficient and *t*-value for each hypothesized relationship. The table indicates that 4 out the 7 possible relationships were statistically significant ($p < 0.001$) and that all the statistically significant relationships were positive in direction. The results indicate that of the three learning environment scales, the two scales of teacher support and personal relevance were most likely to influence students' enjoyment of their mathematics lessons and their academic self-efficacy.

Table 6. Standardized path coefficients and t-value for the hypothesized relationships in the research model

Hypothesized relationship	Standardized path coefficient	*t*
Teacher Support → Academic Efficacy	0.15	1.76
Involvement → Academic Efficacy	0.02	0.21
Personal relevance→ Academic Efficacy	0.30	3.47***
Teacher Support → Enjoyment	0.35	3.82***
Involvement → Enjoyment	-0.14	-1.54
Academic Efficacy → Enjoyment	0.77	10.22***
Personal Relevance → Enjoyment	0.34	3.72***

***p<0.001

I also examined regression weights and deleted nonsignificant paths. The paths deleted were from the involvement scale to academic efficacy scale, suggesting that the perceptions of academic self-efficacy is not affected by student involvement. Another path deleted was from involvement to enjoyment of mathematics lesons, again suggesting no causal link between involvement and enjoyment of mathematics lesons. Finally, the path from teacher support to academic self-efficacy was also deleted, suggesting that academic efficacy is not affected by the perceptions of teacher support.

After deleting the nonsignificant paths and correlating the errors in certain pairs of variables, I reestimated the model and accepted it as a final model because it provided a good fit with all significant paths (χ^2 = 1372.34, CFI = 0.93, IFI = 0.93, RMSEA = 0.05) (Table 5). The final model is presented in Figure 2. All factor loadings were significant and generally high, suggesting that measured variables were reliable and valid measures of the latent variables.

The explanatory power of the research model (refer to Figure 1) was assessed by calculating the coefficient of determination (R^2) of the endogenous constructs (Santosa, Wei, & Chan, 2005). Table 7 indicates that 10% of the variation in students' academic efficacy scores in mathematics learning can be accounted for by their perception of their classroom learning environment (teacher support, involvement and personal relevance). Also, 48% of the variance on students' enjoyment of their mathematics lessons can be accounted for by their perception of teacher support, involvement and personal relevance.

Table 7. Coefficient of determination (R^2) of the endogenous

Endogenous Construct	R^2
Academic Self-Efficacy	0.10
Enjoyment of Mathematics Lessons	0.48

Effects on Enjoyment of Mathematics Lessons and Academic Self-efficacy

My main purpose in this study was to examine the effects learning environment variables on college students' enjoyment of mathematics lessons and their academic self-efficacy. I interpreted the structural relationships in the model as the effect of one latent variable on the other. I examined direct and indirect effects for significance and magnitudes (see Table 8). In the initial run, I found that the direct effects of teacher support on academic efficacy, involvement on academic efficacy and involvement on enjoyment of mathematics lessons were very small and not significant, so these paths were deleted one by one in subsequent runs for reasons of parsimony. All paths were significant in the final model (see Figure 2). The largest effect in the model was that of academic efficacy on enjoyment of mathematics lessons (β = 0.77). This result indicated a strong effect of academic efficacy on students' enjoyment of mathematics lessons. Students' enjoyment of mathematics lessons were strongly affected by their perceptions of their academic self-efficacy.

The two learning environment variables (teacher support and personal relevance) both influenced students' enjoyment of mathematics lessons. Teacher support had a moderate direct effect (β = 0.30) on enjoyment of mathematics lessons. This suggests that as students perceive more positive teacher support, they are more likely to enjoy their mathematics lessons. Personal relevance had a moderate direct effect (β = 0.29) and also a moderate indirect effect (β = 0.28), so the total effect of personal relevance on enjoyment of mathematics lessons was large (β = 0.57). This effect indicated that as students perceive their personal relevance as positive, they enjoy their mathematics lessons more.

Table 8. Direct, indirect, and total effects on enjoyment of mathematics lessons and academic efficacy

Scale	Enjoyment of Mathematics			Academic Efficacy		
	Direct	Indirect	Total	Direct	Indirect	Total
Teacher Support	0.30***	–	0.30***	–	–	–
Involvement	–	–	–	–	–	–
Personal Relevance	0.29***	0.28***	0.57***	0.36***	–	0.36***
Academic Efficacy	0.77***	–	0.77***	–	–	–

****p<0.001*

Finally, personal relevance had a moderate direct effect (β = 0.36) on academic efficacy but no indirect effect. Hence the total effect was moderate (β = 0.36). This suggests that students who have positive perceptions on personal relevance are likely to have moderately more positive academic self-efficacy. See Table 8 for a complete pattern of direct, indirect and total effects on enjoyment of mathematics lessons and academic self-efficacy.

DISCUSSION AND CONCLUSION

The purpose of this study was to examine the effects of teacher support, involvement and personal relevance on students' academic self-efficacy and their enjoyment of mathematics lessons. There was strong support for the hypothesized relationships and mediated effects of teacher support and personal relevance on academic self-efficacy and their enjoyment of mathematics lessons. All coefficients were significant and in the theoretically expected direction. The findings of this study suggest that the two aspects of learning environment (teacher support and personal relevance) significantly influence students' enjoyment of mathematics lessons and academic self-efficacy.

Results suggested that students' enjoyment of their mathematics lessons was more positive in classrooms with greater teacher support and personal relevance, and that academic self-efficacy was higher in classes with more personal relevance. This would suggest that, as students get more teacher support and mathematics lessons are made relevant to them, the more likely it is that they will enjoy mathematics lessons. The results also indicated that increased academic self-

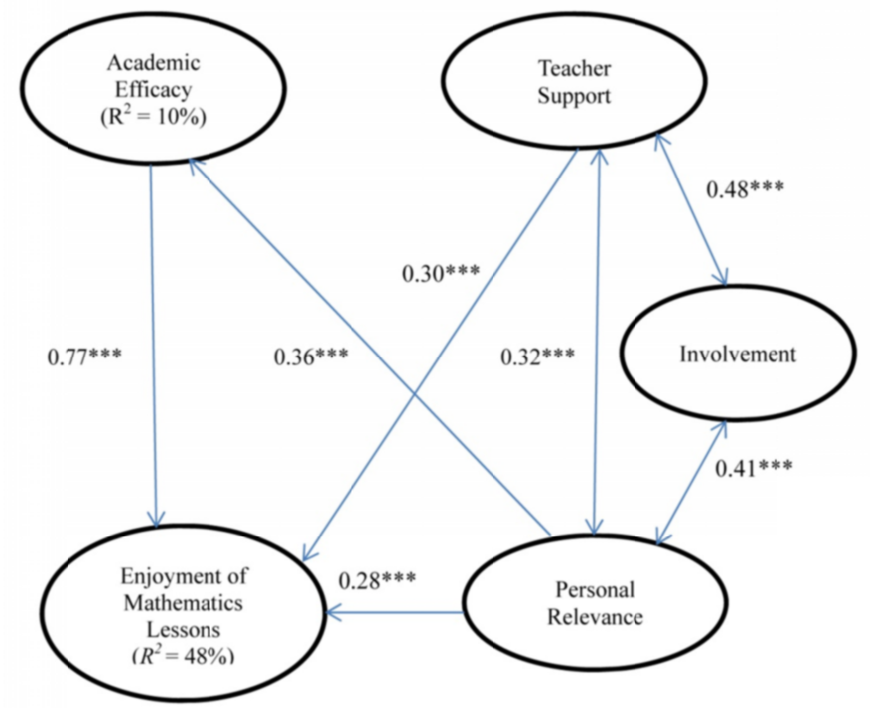

Figure 2. Representation of the revised and final model linking teacher support, personal relevance and academic self-efficacy and enjoyment of mathematics lessons scales.

efficacy is likely with more personal relevance and enjoyment of mathematics lessons. These results reflect past studies in which students' enjoyment and self-efficacy and their perceptions of the learning environment (teacher support and personal relevance) have been found to have positive relationships (Ahmed, Minnaert, van der Werf, & Kuyper, 2010; Fraser, 2012; Lorsbach & Jinks 1999; Sakiz, Pape, & Hoy, 2012).

The study of the total effects revealed the important influences of teacher support and personal relevance on students' enjoyment of mathematics lessons and academic self-efficacy. Results indicated that students' enjoyment of mathematics lessons were strongly affected by their perceptions of their academic self-efficacy. This is consistent with results in recent studies in which Pekrun, Goetz, Frenzel, Barchfeld and Perry (2011) and Sakiz et al. (2012) reported that academic enjoyment was significantly positively associated with students' academic efficacy.

Results of my study indicated significant total effect of perceived teacher support on enjoyment of mathematics lessons. Suggesting that experiencing more teacher support in the mathematics classroom is likely to increase students' enjoyment of their mathematics lessons. This support previous research conducted in Brunei, Singapore, Australia and USA (den Brok, Fisher, & Scott, 2005; Fisher, Waldrip, & den Brok, 2005: Lang, Wong, & Fraser, 2005, Sakiz et al., 2012).

The generalisation of the results to other populations should be made with caution since this study involved a relatively small number of students (352 students, 33 classes from three colleges in Abu Dhabi). The United Arab Emirates is a country with seven emirates (states) with at least five colleges in each emirate and no sample was drawn from any of the other six emirates. It is therefore unclear whether my findings would apply to other college-level institutions in the United Arab Emirates. A further limitation of my study is the limited scope in terms of student outcomes, which included only students' academic self-efficacy and their enjoyment of mathematics lessons. In particular, the absence of any achievement outcomes might be considered as a limitation and the inclusion of which may have enhanced my study.

The research reported in this article is significant because it is one of the few studies to be conducted in the United Arab Emirates that structural equation modeling has been used to develop a comprehensive model representing the relationships among classroom environment and outcomes. The results of this study will hopefully encourage teachers, especially in the United Arab Emirates to improve their classroom environment which will most likely improve their students' outcomes. Also mathematics teachers will be encouraged to provide a learning environment with a cooperative atmosphere in which students feel that they are supported by their teachers and mathematics lessons are made relevant to them. The results of my study have the potential to influence educators and policy makers to focus on stimulating a number of learning environment elements, such as teaching methods that involve cooperative work, active participation in the learning process and an atmosphere in which all students will perceive their teachers as supportive and approachable which will hopefully increase students enjoyment of their lessons and improve their confidence in academic competence.

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6. STUDENTS' LEARNING ENVIRONMENT, MOTIVATION AND SELF-REGULATION: A COMPARATIVE STRUCTURAL EQUATION MODELING ANALYSIS

INTRODUCTION

Over the past 40 years, research has consistently shown that the quality of the classroom environment is an important determinant of student learning (Fraser, 2007, 2012). That is, students are likely to learn better when they perceive their classroom environment positively. According to Hanrahan (2002), research on science pedagogy suggests that the dynamics of science classrooms can be influential in alienating students before they even to begin to engage with science concepts. While classroom environment research focuses on perceptions of classroom life, usually from the students' perspective (Fraser, 2007), contemporary research in psychology draws attention to the importance of developing self-belief and self-regulatory capabilities in students (Zimmerman, 2008). Indeed, one of the endeavors of science education is to motivate and empower students by nurturing the belief that they can succeed in science learning and to cultivate the self-regulatory strategies required to help to bring about that success. Urdan and Schoenfelder (2006) propose that enhancing student motivation requires attention to the key features of the classroom learning environment that are likely to influence student motivation. Zimmerman (2008) contends that the effect of classroom stimulators and constraints on changes in students' self-regulated learning is important and should be studied further. Our study took up these suggestions by investigating psychosocial aspects of learning environments and their influence on students' development of motivation and self-regulation in science learning.

According to Schunk and Zimmerman (2007), students' social environments can influence their affective domains and behaviours. Additionally, teachers, who are an integral component of the classroom environment, can inspire students by creating a favourable classroom environment in which they feel personally efficacious and motivated, and, therefore, work harder to succeed. Hence, our study aimed to inform practitioners and policy makers about which factors within the learning environment are likely to enhance student motivation and self-regulation in science learning. This information could guide teachers in directing

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 115–133.

and focusing the science classroom environment in an attempt to cultivate the motivation and self-regulatory strategies required to succeed in science learning.

LEARNING ENVIRONMENT

It has been estimated that students spend up to 15,000 hours in classrooms by the time that they complete high school (Fraser, 2001; Rutter, Maughan, Mortimore, Outson, & Smith, 1979). Therefore, what happens within these classrooms, such as the nature of the teaching and learning and the interactions experienced by students, are likely to have a profound impact on a range of outcomes. Despite the importance of what goes on in the classroom, science educators tend to rely heavily on achievement and other outcomes which do not provide a complete picture of the educational process (Fraser, 2001, 2012). Although the learning environment is a subtle concept, there has been much progress in the conceptualisation, assessment and examination of its determinants and effects.

The notion that there exists a learning environment which mediates aspects of educational development began as early as the 1930s; when Lewin (1936) recognised that the environment and the interaction of the individual were powerful determinants of behaviour. Lewin initiated this shift in the study of psychology from a focus on the individual to a focus on processes between individuals (Crosbie-Brunett & Lewis, 1993). Murray (1938) extended Lewin's work with his Needs-Press Model which asserts that an individual's need is provoked directly by the occurrence of one or more effective presses from the individual's environment.

Moos (1974), as part of his work in a range of environments, delineated three general dimensions that characterize any human environment: personal relationships, personal growth and system management. Whilst the personal relationships dimension focuses on the different types and strengths of relationship in the environment, the personal growth dimension is concerned on the availability of opportunities for personal development and self-enhancement. The final dimension, system management, examines the degree to which the environment is orderly, maintains control and is responsive to change. Research specifically on classroom learning environments took off over 40 years ago with the development of well-validated and robust classroom environment instruments to measure students perceptions, largely based on Moos' three pertinent dimensions (Fraser, 1998). The What Is Happening In this Class? (WIHIC), selected for use in the present study, combines scales from past learning environment with scales of contemporary relevance to ensure good coverage of the three dimensions developed by Moos (Aldridge, Fraser & Huang, 1999). The WIHIC is comprised of three scales measuring personal relationships (student cohesiveness, teacher support and involvement), three scales measuring personal development (investigation, task orientation and cooperation) and one scale measuring system maintenance and change (equity). Further information with respect to these psychosocial learning environment scales is provided in the instruments section.

Research in the domain of classroom learning environment has made significant contributions to the field of education, including program evaluation (Martin-Dunlop & Fraser, 2008; Nix, Fraser, & Ledbetter, 2005; Wolf & Fraser, 2008), teacher action research (Aldridge & Fraser, 2008; Aldridge, Fraser, Bell, & Dorman, 2012) and cross-national studies (Aldridge et al., 1999; Fraser, Aldridge, & Adolphe, 2010). In particular, associations between outcome measures and classroom environment perceptions have been replicated for a variety of cognitive and affective outcomes, with a range of instruments, across numerous countries and at all grade levels (Fraser, 2007, 2012). The consensus is that student perceptions of the classroom environment account for appreciable amounts of variance in learning outcomes, often beyond that attributable to student background characteristics (Dorman, 2001; Fraser, 2007). Therefore, to stimulate and optimize student learning, knowledge of students' perceptions of learning environment and how these factors influence their learning is crucial for both teachers and educational researchers.

Student motivation and self-regulation are important affective outcomes that are necessary for the improvement of science classrooms. Past research has reported that the classroom environment has a strong association with academic efficacy (Dorman, 2001; Dorman & Adams, 2004). We felt that the influence of psychosocial learning environment on students' learning goal orientation, task value and self-regulation warranted further investigated. Furthermore, the interactions elucidated in the social cognitive theory suggest that relevant aspects of the learning environment could influence both student motivation and self-regulation. This theoretical basis, coupled with the limited number of studies related to the influence of learning environment on student motivation and self-regulation, provided the impetus for our research. Hence, we investigated salient psychosocial features of classroom environment that could influence student motivation and self-regulation in science learning.

MOTIVATION AND SELF-REGULATION

Research has indicated that motivated students are the key to successful learning engagement in classrooms (Pajares, 2001, 2002; Pajares & Schunk, 2001). Specifically, in science learning, research indicates that students' motivation plays a pivotal role in their conceptual change processes, critical thinking, learning strategies, and science achievement (Glynn, Taasoobshirazi, & Brickman, 2007; Kuyper, van der Werf & Lubbers, 2000; Lee & Brophy, 1996; Napier & Riley, 1985; Pintrich, Marx, & Boyle, 1993; Wolters, 1999). Three components of motivation, learning goal orientation, task value and self-efficacy, have been found to be related to student engagement in self-regulated learning (Zimmerman, 2002).

Learning goal orientation involves the student's purpose in developing competence in the subject and focuses on learning, understanding and mastering tasks (Midgley, 2002). Prevailing evidence from past research has indicated that students' learning goal orientation is likely to influence a range of positive learning outcomes including student achievement (Brookhart, Walsh, & Zientarski, 2006;

Kaplan & Maehr, 1999, 2007). Academic task value beliefs are an integral element that structures students' motivation to learn (Eccles 1983; Pintrich, 1989; Pintrich & De Groot, 1990). Students who are convinced that the learning activity is important, appealing and useful tend to be more cognitively engaged to learn, put in greater effort and persevere longer to complete a learning task (Schunk & Zimmerman, 2007; Wolters & Rosenthal, 2000). Self-efficacy has received much attention in educational research and it has been shown to influence students' academic achievement across various academic areas and levels (Pajares & Urdan, 2006). Previous research has established that science self-efficacy is related to science achievement and engagement with science-related activities (Britner & Pajares, 2006; Kupermintz, 2002; Lau & Roeser, 2002; Pajares, Britner, & Valiante, 2000). Shaughnessy (2004) asserts that teachers who seek to help students to increase their self-efficacy should first attend to the sources underlying these beliefs.

The dearth of research on the influence of classroom environment on academic efficacy was brought to the attention of learning environment researchers by Lorsbach and Jinks (1999) who called for the convergence of these two fields. When Dorman (2001) and Dorman and Adams (2004) took up this challenge, multiple regression analyses of data from mathematics classes indicated that most of the classroom environment scales related positively with academic efficacy. Our research focused on the three motivational beliefs discussed previously, namely: learning goal orientation, task value and self-efficacy (all of which contribute significantly towards student engagement in science learning). We felt that it was important to investigate the classroom learning environment as the genesis of these motivational beliefs and to draw out factors that positively nurture student's learning goal orientation, task value and self-efficacy in science learning.

According to Zimmerman (2002), students' differing level of self-regulation is a key contributor towards individual differences in learning. Motivation theorists argue that research related to self-regulated learning has focused on students' use of cognitive and meta-cognitive strategies while leaving out one of the most important components of self-regulation, namely, sustaining effort until completion of the task (Boekaerts, 1993; Boekaerts & Cascallar, 2006; Corno, 1994; Pintrich, 2000). Effort regulation is the "tendency to maintain focus and effort towards goals despite potential distraction" (Corno, 1994, p. 229). Past research has indicated that effort regulation is a strong determinant of student achievement (Doljanac, 1994; Lee, 1997). Based on this theoretical and research evidence, we have assumed that students' self-regulation of effort is a key component of students' learning engagement in science lessons. Zimmerman (2008) asserts that the effects of learning environment on students' self-regulated learning should be studied further. Our study took up this challenge and filled the research gap in terms of studies of psychosocial aspects of learning environment and its influence on students' development of effort regulation in science learning.

Zimmerman (2000) emphasizes that self-regulatory skills are of little value to students if they cannot motivate themselves to use them. The cyclical phases of Zimmerman's (2002) self-regulated learning theory highlight the major role of self-motivation beliefs in initiating and maintaining self-regulation of learning. In addition, Pintrich (2003), in a review of past research, concluded that research evidence indicates that students who are more academically motivated show higher self-regulation in learning. Hence, our study decided to investigate the role of learning goal orientation, task value and self-efficacy as predictors of students' self-regulation in science learning.

RESEARCH METHOD

Research Model

As a first step the the study aimed to validate the questionnaires used in this study using confirmatory factor analysis. The second step involved assessing a research model, based on both theory and research (discussed in the previous section). The model, presented in Figure 1, hypothesizes that each of the seven psychosocial aspects of the learning environment (student cohesiveness, teacher support, involvement, investigation, task orientation, cooperation and equity) individually influences each of the three motivation constructs (learning goal orientation, task value and self-efficacy) and self-regulation. Additionally, each of the three motivation constructs (learning goal orientation, task value and self-efficacy) is predicted to influence self-regulation in science learning.

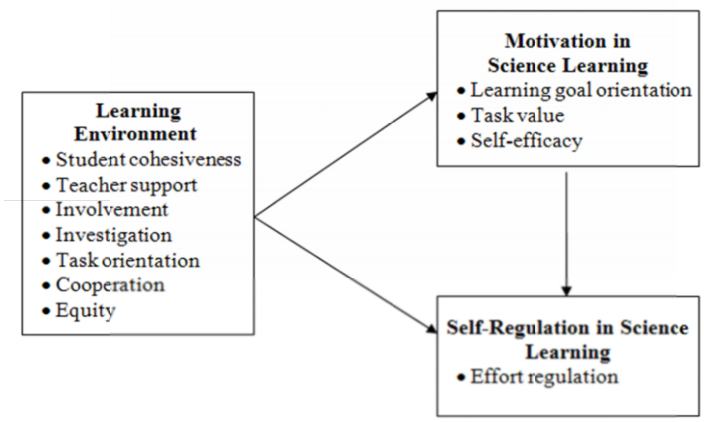

Figure 1. Representation of the research model linking learning environment, motivation in science learning and self-regulation in science learning scales

Participants and procedures

The sample for this study included 1360 students (719 boys and 641 girls) in grades 8, 9 and 10 from five public schools in Perth, Western Australia. To provide a representative sample of lower secondary students in public schools, the schools were selected to encompass students with differing abilities, gender and socio-economic status. Both instruments (described below) were administered, with guidance from the researchers, during one class period in the last quarter of the academic year, by the science teachers.

Instruments

Students' perceptions of the classroom environment were assessed using the What Is Happening In this Class? (WIHIC) questionnaire, which was specifically designed for high school science classes (Aldridge et al., 1999). The WIHIC incorporates the best features of existing instruments through the integration of psychosocial classroom learning environment scales that have been confirmed through past studies as statistically significant predictors of student outcomes (Fraser, 1998). The salient scales were adapted and combined with particular aspects of constructivism and other relevant factors operating in contemporary classrooms to bring parsimony to the field of learning environments research (Aldridge et al., 1999; Dorman, 2008). The reliability and validity of the WIHIC have been supported for samples in Australia and Taiwan (Aldridge et al., 1999), the US (Ogbuehi & Fraser, 2007; Wolf & Fraser, 2008), Indonesia (Fraser et al., 2010), Singapore (Chionh & Fraser, 2009; Khoo & Fraser, 2008), Korea (Kim, Fisher, & Fraser, 2000), United Arab Emirates (Afari, Aldridge, Fraser, & Khine, 2013) and India (den Brok, Fisher, & Koul, 2005).

Of all of the questionnaires developed in the field of learning environments, the WIHIC is the most widely used. Its impressive validity in a range of contexts and countries has contributed to what has been termed 'band-wagon status' (Dorman, 2008). The final version of the WIHIC consists of seven eight-item scales, namely, student cohesiveness, teacher support, involvement, investigation, task orientation, cooperation and equity. The WIHIC is worded to elicit the student's perception of his/her individual role within the classroom. Table 1 provides, for each WIHIC scale, a description, a sample item and its classification according to Moos's schema.

To assess students' motivation and self-regulation in science learning, we used the Students' Adaptive Learning Engagement in Science (SALES), developed by Veyaluthan, Aldridge and Fraser (2011). The SALES has 32 items with eight items in each of the four scales of learning goal, task value, self-efficacy and self-regulation. Table 2 provides a scale description and a sample item for each scale of the SALES instrument.

Table 1. Scale description, sample item and Moos classification for each WIHIC scale

Scale name	Scale description	Sample item	Moos's Schema
Student cohesiveness	The extent to which students know, help and are supportive of one another.	I make friendships among students in this class.	R
Teacher support	The extent to which the teacher helps, befriends, trusts and is interested in students.	The teacher takes a personal interest in me.	R
Involvement	The extent to which students have attentive interest, participate in discussions, do additional work and enjoy the class.	I give my opinions during class discussions.	R
Investigation	The extent to which skills and processes of inquiry and their use in problem solving and investigations are emphasised.	I solve problems by using information obtained from my own investigations.	P
Task orientation	The extent to which it is important to complete planned activities and to stay on the subject matter.	Getting a certain amount of work done is important to me.	P
Cooperation	The extent to which students cooperate rather than compete with one another on learning tasks.	I cooperate with other students on class activities.	P
Equity	The extent to which students are treated equally by the teacher.	I am treated the same as other students in this class.	S

Note. R = Relationship, P = Personal Development, S = System Maintenance and System Change.
Source: Aldridge, Fraser & Huang (1999)
Response alternatives: Almost Never, Seldom, Sometimes, Often and Almost Always

Table 2. Scale description and sample item for each SALES scale

Scale	Scale description	Sample item
Learning goal orientation	The degree to which the student perceives him/herself to be participating in a science classroom for the purpose of learning, understanding and mastering science concepts, as well as improving science skills.	In this science class, it is important for me to learn the science content that is taught.
Task value	The degree to which the student perceives the science learning tasks in terms of interest, importance and utility.	In this science class, what I learn can be used in my daily life.
Self-efficacy	The degree of confidence and beliefs that a student in his/her own ability to successfully perform science-learning tasks.	In this science class, even if the science work is hard, I can learn it.
Self-regulation	The degree to which the student controls and regulates his/her effort in science learning tasks.	In this science class, even when tasks are uninteresting, I keep working.

Response alternatives: Almost Never, Seldom, Sometimes, Often and Almost Always

Data Analysis: Confirmatory Factor Analysis and Assessment of Research Model

Traditionally, two approaches have been used in structural equation modeling analysis; covariance-based and variance-based techniques (Henseler, Ringle, & Sinkovics, 2009). Covariance structure analysis is exemplified by many available software programs including LISREL (Jöreskog & Sörbom, 1993), AMOS (Arbuckle, 1994), EQS (Bentler, 1995) and Mplus (Muthén & Muthén, 1994) whereas variance-based technique is represented by the software programs LVPLS (Lohmöller, 1984), PLS-Graph (Chin, 2001), SmartPLS (Ringle, Wende, & Will, 2005), and VisualPLS (Fu, 2006). Deciding which SEM approach to use often presents a challenge for researchers (Hulland, Ryan, & Rayner, 2009). Although there are sufficient user guides for both types of SEM software programs, there is little information to help the researcher to compare usability and outcomes of these programs. Hence, this study used both approaches to compare the findings and to allow the examination of the relative performance of each of the techniques. The aim was to offer some guidelines to future researchers by providing a comparative analysis of the results obtained using the covariance-based AMOS and variance-based PLS-Graph SEM techniques.

PLS-Graph (Version 3.0), used in this study, has been recommended as a powerful statistical tool for prediction-oriented research (Hensler, Ringle, & Sinkovics 2009). PLS is highly applicable in theory development, in particular, examining exploratory research models, because it has higher levels of statistical power as compared to covariance-based SEM such as AMOS (Hair et al., 2011). Due to the emphasis on theory building and predictive accuracy in PLS, the goodness-to-fit indices, used in AMOS, is not conducted as a part of PLS analysis (Chin, 1998; Gefen et al., 2000; Henseler et al., 2009). Another advantage of PLS is that it makes minimal distribution assumptions (Chin, 1998). However, despite the growing number of studies utilising PLS, some researchers view the method as less rigorous and, therefore, less suitable for examining relationships between latent variables (Hair et al., 2010).

Amongst covariance-based SEM, AMOS (Version 17), used in this study, has two major advantages. First, AMOS combines SPSS software is familiar to many researchers. Second, AMOS is user-friendly involving icons as the operation interface. The covariance-based approach of AMOS shifts the emphasis from predictive modeling to theory testing, since the objective of AMOS is to explain the covariance of all of the indicators used in a model (Fornell, 1989; Falk & Miller, 1992). The technique focuses on estimating a set of model parameters in such a way that the difference between the theoretical covariance matrix and the estimated covariance matrix is minimized (Rigdon, 1998). AMOS develops a theoretical covariance matrix, based on a specified set of structural equations making it highly suitable for theory confirmation. However, AMOS estimation requires a set of assumptions to be fulfilled, including the multivariate normality of data and minimum sample size (Diamantopoulos & Siguaw, 2000).

The SEM analysis, for the present study, included both confirmatory factor analysis and the assessment of the research model. First, for the confirmatory factor analysis, SEM assessed the properties of the measurements utilized in the research model to achieve convergent and discriminant validity. All items from the two questionnaires were regarded as part of the regression model and analyzed simultaneously (Chin, 1995; Gefen et al., 2000). Then, the assessment of the explanatory power of the research model was conducted by estimating the variance associated with the endogenous constructs (dependent variables or consequents). Finally, path coefficients and *t*-values for the hypothesized relationships were calculated to evaluate the magnitude and statistical significance of the relationships.

RESULTS

Confirmatory Factor Analysis

An important requirement of covariance-based SEM analyses is that the data are multivariate normal (Byrne 2010). The value of the Mardia's coefficient (a standard measure of multivariate normality) obtained in this study, using AMOS, was 238.36. This value, as required, was less than [p (p + 2)] where p = total number of observed indicators; 88(90) = 7,920 (Raykov & Marcoulides, 2008). Therefore the requirement of multivariate normality was satisfied and the data considered fit to be analysed by AMOS.

Convergent validity assesses whether scores on items, assessing a single construct are strongly intercorrelated and measure the same underlying dimension. For both PLS and AMOS, items are examined for their loadings, internal consistency reliability and the average variance extracted to indicate convergent validity (Fornell & Larcker, 1981). The loading for each individual item indicates its correlation with its respective construct. Low loading items will decrease the correlation between the items in the construct and increase the level of random error (Nunnally, 1978). As such, this procedure enables the researcher to identify and eliminate items that could lead to an increase in the construct's level of random error (Fornell & Lacker, 1981). In confirmatory factor analysis, the item loadings typically are higher than for exploratory factor analysis because the pattern of item loadings is pre-specified (Gefen & Straub, 2005). In SEM, the minimum requirement suggested for item loadings is 0.7 (Barclay, Higgins, & Thompson 1995; Chin, 1998; Hulland, 1999).

All item loadings for the PLS analysis were found to be above the recommended cut-off point except for items SC2, SC7, SC8 and SR5. Hence, after the first PLS run, these four items were discarded. When the refined set of items were again analyzed using PLS, all loadings were found to be above the cut-off point of 0.70. In the AMOS analysis, twelve items, the earlier four indicated in the PLS analysis, as well as items SC2, SC3, SC7, SC8, IVT3, IVT5, IVT7, IVT8 LG4, LG7, TV7 and SR5, had loadings lower than the minimum requirement. The items were similarly refined to ensure that all of the items had loadings above 0.70.

Results of internal consistency analysis for each factor for both the PLS and AMOS analysis indicated that all of the factors exceeded the minimum reliability value of 0.7, as suggested by Fornell and Larcker (1981). The final criterion for convergent validity was a measure of average variance extracted (AVE) for each factor. Fornell and Larcker (1981) and Nunnally (1978) specify that, as a rule of thumb, a minimum value of AVE as 0.5. The results of the statistical analysis showed that the AVE values for all scales in both PLS and AMOS analysis were above 0.5. Therefore, the measurement properties satisfied all three necessary criteria of convergent validity.

The criterion of discriminant validity was that the square root of average variance extracted (AVE) for each construct is larger than the inter-construct correlation. The PLS data analysis results supports the discriminant validity because, for each construct, the square root of the AVE for each construct was larger than its correlation with other constructs. In the AMOS analysis, this criterion was also met except for the correlation between the student cohesiveness and cooperation scales (0.67) which were slightly higher than the AVE for SC (0.65). Overall, however, the discriminant validity analyses ensured that the individual constructs in the questionnaires were discriminated from each other.

Assessment of the Research Model

The results for the analysis of the structural model for AMOS, together with the recommended level of acceptable fit and the fit indices for the research model in this study are summarized below in Table 3. All of the values satisfied the recommended level of acceptable fit, with the exception of the χ^2. Hair et al. (2010) noted that, as the sample size increases, there is a tendency for the χ^2 to indicate significant differences. For these reason, the ratio of χ^2 to its degrees of freedom (χ^2/df) was used, with a ratio of 5 or less being indicative of an acceptable fit between the hypothetical model and the sample data. The results of the model fit, as shown by the various fit indices in Table 3, indicate that the research model fits the data well.

Table 3. Results of the model fit of the measurement model

Model fit indices	Values	Recommended guidelines	References
χ^2	10290.53 $p< 0.001$	Nonsignificant	Joreskog & Sorbom (1993); Klem (2000); Kline (2010); McDonald & Ho (2002); Meeuwisse, Severiens & Born (2010);
χ^2/df	2.80	< 3	Hu &Bentler (1999); Kline (2010);
TLI	0.92	≥ 0.90	Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002);
CFI	0.92	≥ 0.90	Bollen (1989); Byrne (2010); Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002);
RMSEA	0.036	< 0.05	Browne & Cudeck (1993); McDonald & Ho (2002);
SRMR	0.053	< 0.05	Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002)

The explanatory power of the research model (outlined in Figure 1) was assessed by calculating the coefficient of determination (R^2) of the endogenous constructs (Santosa, Wei & Chan, 2005). Falk and Miller (1992) proposed that the minimum R^2 should be 0.10. Table 4 indicates that, for both the PLS and AMOS analysis, all of the R^2 values were higher than this requirement. The findings imply that 52% (PLS) and 64% (AMOS) of the variation in students' self-efficacy scores in science learning can be accounted for by their perceptions of their classroom learning environment. The percentage of variation in students' scores attributed to psycho-social elements in their classroom learning environment for the task value and learning goal orientation scales were 44% and 50%, respectively, for the analysis with PLS, and 55% and 61%, respectively, for the analysis with AMOS. In addition, for both the PLS and AMOS analysis, the overall model explained a substantial 69% of the variance on students' self-regulation in science learning.

Table 4. Coefficient of determination (R^2) of the endogenous constructs

Endogenous Construct	R^2 (PLS)	R^2 (AMOS)
Task Value (TV)	0.44	0.64
Learning Goal (LG)	0.50	0.61
Self-efficacy (SE)	0.52	0.55
Self-regulation (SR)	0.69	0.69

The standardized beta coefficient of ordinary least squares regressions for each path in the structural model was used to determine the significance of the path. According to Hair et al. (2011, p. 147), "significant paths showing the hypothesized direction empirically support the proposed causal relationship". Table 5 reports the t-value for each hypothesized relationship. The table indicates that, for the PLS analysis, 18 of the 31 possible relationships were statistically significant ($p<0.05$) and that all statistically significant relationships were positive in direction. In the AMOS analysis, however, only seven of the 31 possible relationships were significant. All seven of the significant relationships for the AMOS analysis were significant in the PLS analysis.

The first 28 hypotheses were related to whether psychosocial features of the classroom environment influenced students' motivation and self-regulation in science learning. The PLS results indicate that, of the seven learning environment scales, the three scales of student cohesiveness, investigation and task orientation were the most likely to influence students' learning goal orientation, science task value, self-efficacy and self-regulation in science learning. For the AMOS analysis the results indicate that students' perception of task orientation was the most likely learning environment factor to influence their motivation and self-regulation in science learning.

Table 5. t-value for the hypothesized relationships in the research model for analysis using PLS and AMOS

Hypothesized relationship	*t* (PLS)	*t*(AMOS)
Student Cohesiveness (SC) → Learning Goal (LG)	2.33**	-0.257
Student Cohesiveness (SC) → Task Value (TV)	2.69**	-0.633
Student Cohesiveness (SC) → Self-efficacy (SE)	2.02*	0.991
Student Cohesiveness (SC) → Self-regulation (SR)	2.79**	2.366
Teacher Support (TS) → Learning Goal (LG)	1.73*	3.009
Teacher Support (TS) → Task Value (TV)	3.99***	5.530***
Teacher Support (TS) → Self-efficacy (SE)	0.48	0.056
Teacher Support (TS) → Self-regulation (SR)	0.45	1.363
Involvement (IVT) → Learning Goal (LG)	0.57	0.846
Involvement (IVT) → Task Value (TV)	0.08	0.267
Involvement (IVT) → Self-efficacy (SE)	4.59***	5.530***
Involvement (IVT) → Self-regulation (SR)	1.32	-2.582
Investigation (IGT) → Learning Goal (LG)	3.32***	-0.593
Investigation (IGT) → Task Value (TV)	3.49***	1.832
Investigation (IGT) → Self-efficacy (SE)	3.72***	2.028
Investigation (IGT) → Self-regulation (SR)	3.57***	2.535
Task Orientation (TO) → Learning Goal (LG)	13.92***	15.342***
Task Orientation (TO) → Task Value (TV)	7.77***	13.266***
Task Orientation (TO) → Self-efficacy (SE)	10.04***	14.756***
Task Orientation (TO) → Self-regulation (SR)	9.64***	13.042***
Cooperation (CP) → Learning Goal (LG)	0.27	-2.237
Cooperation (CP) → Task Value (TV)	1.57	-2.698
Cooperation (CP) → Self-efficacy (SE)	1.34	-2.142
Cooperation (CP) → Self-regulation (SR)	0.57	-2.371

Equity (EQ) → Learning Goal (LG)	1.07	-0.249
Equity (EQ) → Task Value (TV)	1.22	-0.050
Equity (EQ) → Self-efficacy (SE)	1.39	0.726
Equity (EQ) → Self-regulation (SR)	0.82	-2.112
Learning Goal (LG) → Self-regulation (SR)	2.11*	1.189
Task Value (TV) → Self-regulation (SR)	2.29*	0.750
Self-efficacy (SE) → Self-regulation (SR)	3.98***	7.042***
Notes: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$		

The research also examined the effect of the motivational constructs on students' self-regulation in science classrooms. For the PLS analysis, all three motivational constructs strongly influenced students' self-regulation in science learning. The AMOS results, however, indicated that students' self-efficacy was the most likely motivational factor to influence students' self-regulation in science learning.

Finally, the research compared the results of the two SEM approaches. The findings indicated that the PLS analysis could be less stringent than the AMOS analysis. Although seven of the hypothesised relationships were statistically significant, 11 additional statistically significant relationships were identified in the PLS analysis. The comparison analysis indicates that the relationships with a *t*-value less than 3.99 are indicated as significant in PLS but are not significant for the AMOS analysis. All of the statistically significant relationships are discussed further in the following sections for their possible implications for science teaching.

DISCUSSION AND IMPLICATIONS OF THE RESULTS

Our findings for both the PLS and AMOS analysis suggest that task orientation significantly influences students' learning goal orientation, task value, self-efficacy and self-regulation in science learning. As shown in Table 1, task orientation is from Moos's (1974) personal growth dimension which emphasizes students' accessibility to opportunities for personal development and self-enhancement. The influence of task orientation on students' motivation and self-regulation in science learning suggests that students need to be aware of the importance of completing planned activities and staying on the subject matter. The results imply that it is time well spent when teachers encourage students to get a certain amount of work done in class. In addition, the results indicate that teachers wishing to improve motivation should highlight to students the goals of each activity and ensure that students understand what they are required to accomplish in each task. The findings support Middleton and Midgley's (2002) suggestion that, for students to succeed in academic tasks, teachers need to apply academic press by constantly challenging students to understand what is being taught in class and to complete their assigned work.

Both the PLS and AMOS results indicate that teacher support (the extent to which the teacher helps, befriends, trusts and is interested in the student) has a statistically significant influence on students' task value. The influence of teacher support on task value suggests that teachers play a major role in helping students to recognize the value of the tasks that they are undertaking in class. The implications are that, if teachers are helpful, friendly and trustworthy to students, students' science task values are likely to increase.

The findings for both the PLS and AMOS analysis indicates that involvement has a statistically significant influence on students' self-efficacy in science learning. This finding makes intuitive sense because students who are involved in classroom activities that encourage them to ask questions, give opinions and explain ideas, are more likely to have confidence in their science abilities. The strong influence of involvement on self-efficacy suggests that teachers who provide opportunities for students to take part in peer and class discussions are likely to elevate their students' confidence level. However, it is important to keep in mind Britner and Pajares's (2006) recommendation that student involvement should be tailored to the abilities of individuals to ensure confidence building and success and to minimize efficacy-diminishing failures.

Finally, the finding that self-efficacy is a strong predictor of students' self-regulation in science learning is consistent with Zimmerman's (2002) self-regulated learning theory which contends that self-efficacy beliefs are the precursor to self-regulated learning. The results suggest that promoting students' self-regulation in science learning could be more successful with prior emphasis on increasing self-efficacy in science learning. Urdan and Schoenfelder (2006) argue that student motivation is influenced not only by students' individual differences but also by the social and academic features of the classroom learning environment. They suggest that altering controllable factors such as the curriculum, teaching style and school or classroom policies could enhance student motivation towards learning. The results of our study imply that, to encourage self-regulated learners in lower secondary science classes, educators must first implement strategies that could increase students' self-efficacy in science learning.

Our comparative analysis using PLS and AMOS based SEM, indicates that the results are similar for both the confirmatory factor analysis and the assessment of the research model. However for the hypotheses testing, AMOS provided a more rigorous SEM approach, whereby only seven of the 18 statistically significant findings for the PLS analysis were also significant for the AMOS analysis. The results support Henseler et al.'s (2011) suggestion that, rather than being competitive, variance-based PLS and covariance-based AMOS are complementary SEM approaches. Joreskog (1982) contends that PLS is primarily intended for causal-predictive analysis in situations of high complexity but low theoretical information. PLS was used in the present study because it is a prediction-oriented, theory building exploratory research, with a complex research model emerging from a review of literature. However, when prior theory is strong and further testing and development is the goal, covariance-based AMOS is the most appropriate approach (Hair et al., 2011; Henseler et al., 2011). In this study, the concurrent AMOS analysis supported the PLS findings and provided more stringent results to validate the research model and to confirm the statistically significant relationships. The two approaches complemented each other and provided rigor to the analysis.

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7. IN/OUT-OF-SCHOOL LEARNING ENVIRONMENT AND SEM ANALYSES USAGE ATTITUDE TOWARDS SCHOOL

IN- AND OUT-OF-SCHOOL FACTORS AFFECTING ATTITUDES TOWARDS SCHOOL

What Are School Attitudes Related to?

There are many factors such as teacher behaviors, school rules, classroom environment, student family, the student himself/herself, teaching process, exams taken and evaluation processes thought to be influential on attitudes towards school. To what extent are these factors influential on forming attitudes towards school? Or, to what extent can these factors account for attitudes towards school? Such questions can be answered to some extent within factor analyses. When you asked a student what his/her attitudes towards school are and to explain what he/she feels about school, he/she can make explanations based on above-mentioned factors. In different environments or cultural structures, factors determining attitudes towards school and between-factor relationships can differentiate. For instance, factors such as physical conditions of a school or the distance between the school and the house and availability of cutting-edge technologies are also related to school attitudes and reactions towards these factors can also vary depending on different socio-cultural environments. Moreover, at different levels of schooling, reactions towards factors can differentiate. At that point, the following questions or similar ones should be answered:

Will the test items to be developed related to attitudes towards school be prepared based on local considerations or universal considerations? If they are to be developed based on local considerations, it will be natural to write a large number or different factors suitable for the given socio-cultural environment. If the child's relationships with the teacher are to be considered one of the factors or variables, then the responses to be given to an item written in relation to this factor may change from one culture to another. For instance, the responses to be given to this statement "I can have an eye contact with my teacher within the class environment" may vary depending on the culture. Zalaquett, McHatton and Cranston-Gingras (2007) reported that some migrant students experience difficulties speaking with unfamiliar people and avoid making eye contact with an authority figure or older person as a sign of respect. In some societies, there are similar attitudes adopted as a sign of respect. For instance, in some societies, a father's being affectionate to his children in the presence of his own father is

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regarded as a sign of disrespect to the grandfather. In societies where avoiding an eye contact with older people or authority figures is considered to be a sign of respect, the responses to be given to the above-mentioned statement may not be directly related to attitudes towards school. Moreover, for which level of schooling will the test to be developed be prepared? Without doubt, components of the attitudes of pre-school children and young children will naturally be different from those of the attitudes of university students or adults.

Attitudes

What will our measurement tool be designed to measure? Achievement?, Ability?, Intelligence? or Attitude? If the purpose is to design a measurement tool to evaluate attitudes towards school, then the content of the attitude should be carefully examined. Eagly and Chaikens's widely cited definition of the term of attitude, "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (as cited in Wittenbrink, 2007). The term attitude refers to global and enduring favorable or unfavorable predispositions toward a stimulus or class of stimuli (Wittenbrink, 2007). The term attitude may be defined as a learned predisposition ('set') to evaluate or react consistently in a particular manner, either positively and negatively, to certain persons, places, concepts, or things (Roeckelein, 1998).

In attitude studies, the widely accepted belief is that there are three components of attitude (Kruglansky, 2007; Roeckelein, 1998). These three components are affective/evaluative, cognitive/belief, and behavioral/action. According to three component-model, attitude expresses people's feeling, belief and past behaviors regarding the attitude subject. Through the process of self-perceptions and cognitive dissonance, people tend to decide that they like something when they can recall doing it often.

It is also difficult to identify each component of attitude with certain limits in itself. For these reasons, attitudes are thought with some concepts and sometimes they are confused. Cognitive responses of a nonverbal kind are more difficult to assess, and the information they provide about attitudes is usually more indirect (Aizen, 2005). In his study, Aizen investigated responses used to infer attitudes, cognition, affect and response mode in conation dimension and categories of response. The fact that there are three components of attitudes and the responses to attitude objects are both verbal and nonverbal makes it difficult to distinguish attitudes from other concepts. In Aizen's (2005) study, there are concepts such as belief, perceptual reaction, behavioral intention, and overt behaviors within three-dimensioned attitudes. This situation shows the boundaries of attitude concept and its relation with other concepts. Eagly and Chaikens' widely cited definition states that attitude is 'a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor' (as cited in Wittenbrink, 2007).

While forming the school attitude items, these three components of attitude should be considered. For example, I feel myself lucky as I am a student in this school (effective component), Negative attitudes of the people in my close circle towards school affect my eagerness negatively (cognitive component), Teachers are only interested in hard working students (behavioral component). Attitude items should be constructed in such a way as to cover these three components.

School Attitude

The term attitude may be defined as a learned predisposition ('set') to evaluate or react consistently in a particular manner, either positively and negatively, to certain persons, places, concepts, or things (Roeckelein, 1998). What is meant by school attitude? It is a complex term. It can be claimed that the studies in school attitudes can only partly explain. This may be due to the fact that it is a higher level concept in school system approach rather than concept misunderstandings and misconceptions. The variables concerning attitudes towards school cannot be thought separately from the classroom learning environment, school environment, social environment and classroom climate. Attitudes towards school are related to not only the classroom learning environment but also the school environment. Studies of student perspectives and behaviors show that many factors affect attitudes towards school. Factors such as parental attitude, school belongingness, school bonding, peer relationship, liking teachers, friendship, teaching atmosphere and their impacts are explored below as they relate to student attitudes towards school. In general, school attitudes are related to in- and out-of school factors and personal/individual factors (Şeker, 2011).

When the related studies are scrutinized, it is difficult to isolate the concept of school attitudes from among many related concepts. When affective, cognitive and behavioral dimensions of attitude are taken into account, it may be more difficult to discern it from other concepts. It has been observed that the concepts that can be deemed to hold the same meaning for school attitudes are expressed using different concepts. For example 'social environment' can be used equally with 'classroom climate' (Anderson, Hamilton, & Hattie, 2004). In Dorman's (2009) study, school environment and school climate have been used similarly. "Classroom learning environment is defined as students' perception of or reaction to their learning tasks and classroom instruction" (as cited in Waxman & Huang, 1998). School attitude can involve student reactions to learning tasks and classroom instructions. It seems that the concept of attitude towards school is more comprehensive than concepts such as student's perceptions of teaching and learning environment, and 'classroom learning environment'. The factors such as peer groups and parental approach to school are considered within school attitude. School attitude is combined with both in-school and out-school variables, such as family and peer groups, and it cannot be confined to the classroom learning environment alone. In addition to school attitude, emphasis is given to in-school and out-school learning and the effect of social environment on student's predisposition is depicted. Some factors that can be related to school attitudes are discussed below.

For many of us, the first day at school is special. This is the day which usually makes students and families exited. For some, it is boring and even a nightmare, yet, for some others, it is a day longed for a long time. What are the factors leading to the formation of such different attitudes?

What Are the Factors That May Affect Our School Attitudes?

Our school attitudes might be affected by the school's learning environment or in-school education and instruction, administration and school program. Yet, only in-school factors cannot explain school attitudes sufficiently. The concept of school attitude can be related to in-school factors as well as out of-school factors and personal/individual factors. School attitude was viewed as a combination of both in-school and out-of-school variables, such as family and peer groups, and was not confined to the classroom learning environment alone. Emphasis also was given to in-school and out of-school learning and the effect of the social environment on a student's predisposition.

The Factors Affecting School Attitudes

Thus far, many studies have proved the reasonable assumption that if the attitude of a student towards school is positive, his success at school will be high and if his attitudes are negative, his success at school will be low. The studies conducted in the field have showed that variables such as student's seeing himself as someone belonging to school, interest of the family in school, quality of the classroom teaching and learning processes have varying effects on school success and student's attitudes towards school. As far as we know, in none of these studies, we can see to what extent the factors affecting the attitudes towards school altogether affect the school attitude.

Many factors affecting school attitude affect the attitudes in compliance with each other are examined? For instance, study X can explain the effects of factor A on attitudes towards school, yet it cannot explain the effects of factors B, C, and D that can simultaneously affect the attitudes towards school. Moreover, it cannot explain the effects of factors ABCD in combination. Former studies developed an attitude questionnaire that is very comprehensive and that can examine the effects of many factors affecting the attitudes towards school.

Studies in this field show that many factors affect the attitudes towards school. As it is cited below, it is generally seen that the factors such as parental attitude, school belongingness, school bonding, peer relationship, liking teachers, friendship, and teaching atmosphere affect attitudes towards school. In the study conducted by Holfve-Sabel and Gustafsson (2005), the content of the questionnaire developed to investigate the attitudes of students towards school emphasizes three main areas: (a) Students' interests in school in relation to classroom factors (boredom experienced by students in the classroom, monotonous activities, fun activities, desire to leave the school activities early, unwillingness to come to school, and necessity of knowledge obtained at school); (b) Views of the teachers, teachers' commitment to their promises, teachers with peaceful and nice behavior, teachers helping their students, and their concern for the problems of students; and

(c) relations with the classmates (hostility among students, feeling of loneliness, etc.).

Teacher Competence

Teacher competence can be seen as another factor effective in the formation of attitudes. Developing positive attitudes to learning and strengthening one's self-confidence is of importance, as well as developing other life skills. It is reasonable to assume that teacher competence is related to students' attitudes to school work and learning as well as students' self-confidence and self-conceptions. There are high correlations between teacher competence, school attitudes and self-confidence (Malm & Löfgren, 2006).

Academic Success

Students' sense of achievement and positive attitudes toward the quality of school life are likely indicators of improved school performance (Silins & Murray-Harvey, 2000). Negative attitudes towards school may stem from the failure experienced at school and may affect the school performance (McCoach, 2002). McCoach (2002) states that the best predictor of success in school is aptitude, and it can explain 50% of the variance observed in student scores. This proves that the only factor affecting academic success is not aptitude alone; there are also other factors that influence the success of the student.

There are studies showing the relation between students' attitudes and their academic success (McCoy, 2005; Legum & Hoare, 2004; Bryant et al., 2003; McCoach, 2002; Hung & Marjoribanks, 2005; Hoower-Dempsey, Besler, & Brissie, 1992). However, some studies show that the academic success for one course can be the indication of the student's general attitude towards school. In Reynolds' (2001) study, a relation was found between students' attitudes towards school and their academic success in mathematics. In Maher's (2000) study, highly significant correlations were observed between students' general attitudes towards school and their attitudes towards courses (Science, Mathematics, Social Sciences, Language). On the other hand, in Morrell and Lederman's (1998) study, although students showed positive attitudes towards school, they do not show positive attitudes towards science course. Moreover, a weak correlation is observed between their attitudes towards school and science course. Hence, students' negative attitudes towards a course may not reflect their general attitudes towards school. Attitudes towards school just indirectly affect students' success (Maher 2000).

Correlation studies revealed that if students' attitudes towards an object are positive, it is possible to see weak correlation between this object and the ones to be compared with it. In such studies, great care should be taken while selecting the sample.

Attitudes of Peer Groups

In the study conducted by McCoach (2002, p. 72), high correlations are observed between the attitudes towards school and attitudes of peer groups, motivation and self-regulation. The study shows that the students whose success levels are below average exhibit more negative attitudes towards school than the students whose success levels are above average. Students' having a negative image of the school may be the reason for many other factors to be negatively perceived. Hence, having a positive image of the school may affect the attitudes towards school positively. In Şeker and Kömür's (2004) study, it was found that the students who perceive themselves as unsuccessful tend to perceive classroom atmosphere, teaching environment and the teacher as unsuccessful. Research in the peer relationship literature has indicated that peers might influence learners' attitude and beliefs about school as well as their academic achievement (cited in Nelson & DeBocker, 2008).

Belongingness and School Membership

In Libbey's (2004) study, nine factors (academic tendency of the students, belonging, fairness, out of program activities, liking the school, student voice, peer relations, security and teacher support) are found to be related to the school attitude.

Belongingness mediates student-teacher cooperation and leads to positive school attitude. Positive student-teacher relationship increases students' positive school-related attitude because this promotes a greater sense of school belongingness (Pintrich & Meaher, 2004). Belongingness beliefs were not only related to student achievement. In addition, belongingness was significantly and negatively related to absenteeism when the effect of achievement was controlled. Researchers have been increasingly interested in the relationship between the students' perceptions of belongingness and their resultant motivation and achievement in the school setting (Nichols, 2008). In Goodenow's study, it is observed that school membership has a primary role in student's engagement in academic activities and contributes to student motivation. Goodenow focused primarily on the role of perceived school membership in maintaining student motivation and their engagement in academic activities. Students' sense of belongingness affects their motivation, learning and development (as cited in Anderman & Freeman, 2004)). There are significant points of overlap between school bonding and attitude towards school. Attitudes towards school contain similar elements as attachment to school, school commitment, and attachment to personnel, but it lacks a behavioral component such as a school involvement (Maddox & Prinz, 2003).

Although many student performances depend on the quality of teaching and ability of student, participation in school activities is essential for success. The quality of teaching also affects the participation. Success obtained from the performance influences the level of importance attached to school-related goals.

Gaining identity affects participation as a positive cycle (Leithwood, Aitken, & Jantzi, 2006).

Students Family

Families regard the quality of education as an important criterion in the selecting of school. However, some studies show that selection decision is related to factors such as the situation of general school environment and student activities, which are not academic factors (Kemerer, 1994, cited in Pritchett, Schwartz, & Slate, 2000, p. 3). Grandmond points out that the participation of the family affects student success more than the other factors (cited in Pritchett, Schwartz, & Slate, 2000, p. 3). Both father involvement and mother involvement significantly and independently contributed to positive school attitudes (Flouri, Buchanan, & Bream, 2002). In Kaplan, Turner and Badger's (2007) study, girls who felt that their mothers understood them, showed interest in them and respected their points of view, which are components measured by the Mutuality scale, were likely to have more positive feelings towards school. Girls who have a higher degree of mutuality with their mothers are more likely to enjoy school. Heaven, Mok, Barry and Ciarrochi (2002) express a significant relationship between parental care and school attitude. In Papanastasiou and Elena's (2004) study, it is argued that educational backgrounds of the family and school have influence on students' attitudes. Parents' views will play an important role because parents are an important linking pin between the school environment and the world outside the school (Roelofs, Visser, & Terwel, 2003). The study conducted by Allen and Fraser (2007) shows that the relationship between parents' perceptions of the learning environment and their children's outcomes (attitudes and achievement) was explored and possible associations were identified. The study by Flouri, Buchanan and Bream (2002, p. 579) shows that the perceived involvement of both the parents in-school activities helps the student to develop positive attitudes towards school. A weak relationship is observed between learning and the attitudes of the socially disadvantaged students towards school.

Rousseau, Hassan, Measham, Moreau, Lashley, Castro, Blake and McKenzie (2009) conducted a study called "Family relations, school attitude …" and they employed Resnicowetal's 26-item School Attitude-Bonding (SAB) scale. This scale includes factors related to teachers, academic requirements, and their feelings of safety at school. The findings of the study revealed that a significant negative correlation was noted between family conflict and school attitude. Conversely, the higher the family cohesion, the better the attitude towards school. Significant relationships were observed between the means of intra-family communication and the school attitudes of compliant students.

Extracurricular Activities

Adolescents who participated in extracurricular activities reported higher grades, more positive attitudes toward schools (Darling, Caldwell, & Smith, 2005).

Adolescents who participated in school-based extracurricular activities were more likely to perform better in school, have a more positive attitude toward it, and believe that they will remain in school longer (Darling, 2005). Student must feel safe if they are to become more involved. A safe climate not only leads to increased academic achievement and decreased propensity to drop out, it also significantly increases student involvement (McNeal, 1999).

Measuring a trait requires to go through some phases. Efforts similar to reviewing literature as given above (especially when the trait to be measured is school attitude) are necessary to write criteria and items for the measurement of the given trait. Developing an original test is more difficult than adapting an already developed scale into other languages. The most outstanding difficulty is writing items complying with the theoretical structure of the given trait because theoretical structure of the trait should be well analyzed and its dimensions should be understood well. That is, the theoretical structure proposed for the given trait should be well understood. Otherwise, the findings obtained as a result of a study may not be supported by the theoretical structure of the trait.

The review presented above shows that school attitudes are affected by many in-school and out-of-school factors. Factors actually related to school attitude and those having potential to be related should be determined. Then, care should be taken to include items that are reliable and valid representatives of these factors in the measuring tool.

In the SEM analysis, we examine the factors influencing the school attitude, which in turn affect the attitudes that are in compliance with each other. By using the structural equation modeling (SEM), a model that shows the compliance among these factors and accordingly helps to make more deductions was developed.

What, to What Extent and How Do We Measure?

What is the extent to which the reality is represented through measurement tools? It is possible to put forth some criticisms about whether a measurement tool represents the reality. Even though a "perfect" tool was developed, this tool could be criticized as it is not flexible enough or cannot represent all shades of the reality. Such criticisms have always been done in many fields of social sciences. For example, such questions as "How humane is to educate students according to predetermined goals?", "Is it possible to predetermine the knowledge and skills to be gained by students for all subject areas?" "Can they be same?", can be frequently seen in program development studies where processes come to the fore. On the basis of such questions or criticisms lies the belief that training students according to predetermined target behaviors is not very humane. Moreover, predetermined target behaviors or criteria can make up only limited sample of the related field and in some field they may not represent the reality. Similar criticisms can be directed to studies dealing with academic achievement and affective assessments. Therefore, assessment of school attitude is a hard task.

When we want to determine the scope of a measurement tool, we may encounter some difficulties. For example, when we want to evaluate a drama activity (on which I am not very experienced), it is not enough to consider only performance-related elements such as gestures, mimics, use of voice etc. but technical and design factors such as lighting, design and shape of the stage and costumes should also be taken into consideration. If the study is planned considering these facts, then there are three main factors to be considered to assess the drama activity: (a) performance, (b) technical equipment, (c) design-related factors. Hence, items covering all these factors should be developed and included in the measurement tool. However, is a drama performance only limited to these factors? Despite our limited experience in this field, we can provide answer "no". Hence, inclusion of other factors may reduce the limitations of the measurement tool to be developed. Factor analysis as a tool that brings order to the way we see things by determining which variables are related and which are not (Bryman & Cramer, 2006, p. 325). In addition, including some other variables such as the age group of the participants may result in giving new forms to our measurement tools.

In his book of pragmatism, William James stated that rationalism scorns experimentalism "as it reflects the color richness of the world in a dull manner". In this regard, as in the case of painting the reality as it is in our canvas without losing the brightness of colors, our measurement tool should also reflect the reality and this is only possible when the validity of the instrument is established.

Some Data Collection Approaches to Collect Data Related to the Scope of the Test

Formation of test structure and test items can be made easier by using some methods as the following. For example, the data to be collected,

- Open and closed-ended questions
- Interviews
- Observations
- Action research
- Case study
- Narrative strategies
- Memoirs etc.

These methods can have important contributions to the establishment of criteria for the measurement instrument and construction of test items. Yet, there may be some limitations resulting from the method employed. However, the data collected through these instruments and methods can bring a broad perspective to the scale.

Open-Ended Questions

Closed-ended questions can be answered by using predetermined options such as "I strongly agree", "I strongly disagree" or "yes" or "no" to the pre-constructed items. Open-ended questions can be responded more freely when compared to closed-ended questions. Open-ended questions have an important advantage over the closed-ended ones which is that they reduce the artificiality and lack of variety. Though the analysis of closed-ended questions is relatively easier, they are inadequate for reflecting the colors of the reality. Open-ended questions may also serve the function of selecting items having greater potential to represent the universe. Through open-ended questions, highly different and high number of alternatives can be elicited. Duvarger (2006) calls these questions "cafeteria questions" due to this property. These questions may yield self-service responses-reactions for every participant. Despite this unlimited freedom brought about by open-ended questions, they should be developed based on a reference point. In this way, responses serving the purpose of the test can be elicited.

Narrative, Autobiographies

Methods such as narrative stories, memoirs, autobiographies, case studies can be used to establish item pool. Narratives including information concerning personal experiences are special tools to explain applications and practices (Gudmundsdottir, 1995 cited in Fottland, 2004). Studies based on narratives can help us to understand people's educational reflections on their previously constructed beliefs and they can also serve the function of helping people to reflect on their previously-constructed feelings, opinions and beliefs. Narrative stories provide a rich backdrop for understanding the contextualized situations in which teachers come to know what they know and make the decisions that they do (Rushton, 2004).

In literature reviews, it is seen that case studies are also used as narrative descriptions (Riggs & Ve Sefarin, 1998). Besides narratives and autobiographies, memoirs can also be effectively used during the testing process. Autobiographic narrations of learning and teaching are stories related to how learning and teaching should be (Fottland, 2004). By understanding these narratives, what is happening in learning and teaching environment where students and teachers are present can be comprehended to a great extent.

Autobiographies, narratives, case studies and memoirs, as in open-ended questions, can help to establish trial structures by conducting content analysis and construct items for these trial structures. How is this done? All of the memoirs and/or autobiographies written by the sampling or study group in a study employing these methodologies can generally be read, then, they are classified under certain themes by rereading them. The things classified under some certain themes are in fact trial factor constructs for the tests thought to be developed. After that, expert opinions should be sought whether the memoirs/narratives or open-ended questions are related to a given theme. They can be asked which themes some selected memoirs, narratives, open-ended questions or autobiographic narrations should be included in. In this connection, opinions of different experts are sought relating which factors memoirs are associated with and looking at inter-rater consistencies can help establish the consistency of the whole test.

There are four excerpts below written by students about their memoirs of good education. Let's look at these memoirs.

(Student 1) In science and technology class, the teacher divided us into groups and gave each group a thermometer. Then he took the groups outside the class. The groups measured the temperature. Then the groups made short presentations about their measurements …. At the end of the lesson, I perfectly learned how and under which conditions to use a thermometer …

(Student 2) … Our teacher selected two novels and then determined a voluntary group to work on these novels. We determined the characteristics, superficial aspects etc. and then discussed with the other group … For the first time, we as students were in the fore front. We realized that we have broad viewpoint on novel …

(Student 3) … We carried out an experiment about air-pressure when I was a second-year student at university. We connected the pipes and hung them on the wall. We filled sour-cheery juice into the pipe. Then, we blew into the pipe and in this way we demonstrated air-pressure

(*Student 4) … While we were learning some trends in educational philosophy in the course of introduction to educational sciences, we watched the film "Dead poets society" in order to see the applications of these trends … this was a lesson where I learned without memorizing …*

From the memoirs of the students given below, following criteria can be drawn related to good teaching (without doubt, with larger sample, more criteria can be obtained for the test to be developed):

The first student emphasizes the importance of group interaction and experience. The second student sees group work and active participation as important for good teaching, the third one points out learning by doing and concrete experiences and the fourth student attaches more importance to the use of technology and media. In this respect, the items to be included in the test of good teaching should be designed in such a way as to elicit students' opinions about the trial criteria to be drawn from the above-given memoirs of the students.

Original Test Development

The stages of operation and flow chart to be followed in original test development can be as follows. Test development stages for attitude and ability test are given in Figure 1.

Data Collection for the Structure of the Test to Be Developed

On which topics are data collected? First thing to be considered should be the type of the scale. For instance, if the aim is to develop a scale to evaluate school attitudes, first questions such as "What are school attitudes?", "What is attitude?",

Literature review for the topic to be researched,
Data collection through different instruments

⇩

Writing item (construction of item pool)

⇩

Analysis, selection, arrangement and administration of the items in the pool

⇩

Analyses carried out following piloting for item selection

⇩

Construction of the new test

⇩

Administration of new test

⇩

Statistical analyses following administration

⇩

Construction of the final test

⇩

Seeking for evidence for the reliability and validity of the final test and conducting EFA analyses related to test structure

⇩

Conducting EFA analyses

⇩

Conducting CFA analyses

⇩

Deciding the suitability

⇩

Carrying out standardization works

Figure 1. Stages of operation performed to develop a test for the evaluation of attitude, ability and psychopathologic situations (adapted from the study by Şeker & Gençdoğan, 2006)

"What are its components?" should be answered. If this is done, then it becomes possible to test whether the test or measurement tool complies with this construct. For example, what can be understood from attitudes towards school? When research on learning environment in the literature is investigated, it is seen that some of the criteria related to learning environment are more or less connected with attitudes towards school.

In a study showing that there is a positive relationship between school attitude, class attitude and communication with the teacher and student achievement, some positive relations were also observed between school attitude and the perception of the teacher (Stricland, 1970). It is seen that the concept of school attitude is intertwined with many other concepts. At least some of the variables related to attitudes towards school are embedded within the concepts such as “learning environment” and “classroom environment”, hence, it seems to be necessary to determine the actual borders of the concept intended to be evaluated. School system affect and is affected by many systems such as technology, administration, learning environment and family. Therefore, school attitudes should be related to the learning environment and some other factors. Accordingly, variables concerning attitudes towards school cannot be considered independent of the learning environment of the class, school environment and classroom atmosphere. School attitude can be related to learning environment in the class as well as school environment having the power to influence attitudes towards school. Therefore, the scope of a test aiming to evaluate attitudes towards school should be extended to cover the environment outside the school and the concept of school attitude cannot be restricted to the classroom environment; as a result, such test should be constructed in such a way as to contain both in-class and out of-class factors such as family and peer groups.

In social sciences, many of items in different measurement scales developed independently from each other seem to be very identical to each other. This may be because, the topic for which any test is developed is closely connected with many other topics in social sciences. For example, when the instruments developed to assess learning environment are examined, it is seen that some of the items are related to attitudes towards school. Out of such instruments, Classroom Environment Scale (CES) and the Instructional Learning Environment Questionnaire (ILEQ) are instruments modified to produce a ‘personal form’ of the instrument to elicit an individual student’s responses to his/her role in the class rather than a student’s perception of the class as a whole. The instruments were also modified to focus specifically on students’ perceptions of their content area classes (i.e., mathematics or reading) rather than on their general impressions of school as a whole. The brief description of the CES scale components are involvement, affiliation, teacher sport, task orientation, order and organization and rule and clarity. The CES is a questionnaire that has been widely used in a variety of different educational settings to measure students’ perceptions of their relationships with students and teachers, as well as the organizational structure of the classroom. (as cited in Waxman & Huang, 1998). Cresswell and Fisher (1998) used the ‘School-Level Environment’ (SLEQ) in a study comparing principals’ and teachers’ perceptions of school environment. Fisher and Fraser (1990) helped classroom teachers to identify and work to change elements of their school’s climate (as cited in Johnson & Stevens, 2001). In addition, the SLEQ could serve as a tool for reflection that reinforces or modifies cooperating teacher and student teacher’s learning environment perceptions, both preferred and actual (Kiley & Jansen, 1998). Though including some variables related to school attitude, School-Level Environment Questionnaire (SLEQ) mainly consists of dimensions such as professional interest, staff freedom, and resource adequacy. SLEQ is primarily related to teacher perspective and perception of learning environment.

There are many difficulties involved in the isolation of the concept of school attitude from many other related concepts. Given the fact that attitude has affective, cognitive and behavioral components, it becomes clear how difficult it may be to isolate the concept of attitude from other concepts. Moreover, there are many different school attitude-related terms representing the same concept. For example, 'social environment' can be used interchangeably with 'classroom climate' (Anderson, Hamilton, & Hattie, 2004). In Dorman' study (2009), concept of school environment and the concept of school climate mean the same thing. 'Classroom learning environment' is defined as students' perceiving and reacting to their learning tasks and classroom instruction (as cited in Waxman & Huang, 1998). The term 'classroom climate' is defined as the sum total of all the group processes that take place during teacher–student and student–student interactions. These include interpersonal relationships, emotional intonations and structural aspects of teaching style and classroom organization, teacher expectations of students and attitudes towards them, level of teacher control, disciplinary problems, the gender and age of the students, etc. (Zedan, 2010). Fraser and Tobin (1991) agree that classroom climate affects students' behaviours, levels of knowledge, scholastic achievements, motivation, self-image and attitudes towards a certain discipline, the class and school, and schooling and education as a whole. Therefore, researching the factors that affect classroom environment enables us to identify and understand social processes within the classroom, to explain the behaviour of the students at both the emotional and cognitive level (cited in Zedan, 2010).

School attitude can contain students' reactions to learning task and classroom instructions. We can argue that as a term, school attitude is more comprehensive than some other terms such as 'students' perceptions of teaching and learning environment', 'classroom learning environment' and 'classroom climate'. Within the concept of school attitude, some factors such as peer groups and attitudes of the student family towards school can also be included. What is meant by school attitude is not only in-school factors but also out of-school factors. Sum of these factors can explain school attitude. Thus, during a test development process, factors related to the components of the test should be clearly delineated.

Construction of the Theoretical Basis of Test Structure

Another step to be taken during test development process is to construct the theoretical basis of the thing or trait to be evaluated through the test. Tests should be developed based on some specific theories. For this, review of the relevant literature and investigation of the previously developed measurement tools is a good starting point. This is a good way of establishing an item pool of a study.

Developing tests in the fields of psychology and psychopathology seems to be relatively easier because there is a commonly accepted set of syndromes to be used in psychopathologic studies (Şeker & Gençdoğan, 2006). For example, when studies on depression are examined, it is seen that there is a clarity of the variables taught to be the syndromes of depression. In addition, there are international publications which set some standards for the symptoms accepted as the indicators of psychopathologic problems (e.g. DSM-IV-R; ICD-10). Hence, in a new study, the symptoms can be determined very easily and with great certainty.

However, if there is a field or trait on which relatively little research has been carried out, or there is an elusive concept presenting difficulties in terms of determining its components, it may be difficult to develop a test to evaluate them. For instance, developing a test to measure students' attitudes towards learning environment or students' attitudes towards school or adapting such test into a different language or culture can prove difficult. By examining the previously conducted studies, basic components or factors of these attitudes can be determined. Then they are tested on a piloting group to see the extent to which they are valid for new situation and whether there may be other factors involved. For this purpose, a test-questionnaire study can be carried out as a descriptive study to reveal the existing state. As stated before, having open-ended questions in a test or questionnaire can bring about great flexibility in determining criteria. In case of closed-ended questions, actual state or states may not be determined. Yet, of course, elicited criteria will not be sufficient for the test. The size of two sample groups (study or sampling groups), selection and design of the questions promoting sincere responses may be other factors affecting the number of criteria to be selected and trial questions.

Writing Items – Construction of Item Pool

Following literature review and other data collection efforts about the topic which is the target of the test to be developed, basic criteria, symptoms or indicators should be turned into more explanatory statements to construct the items. For example, we assume that the factors which can be predictors of school attitudes have been determined as a result of literature review, other data collection methods and systematic or unsystematic observations as follows:

Teaching
Classroom environment
Teacher
School rules
Family
Student
Exam
…

After determining the factors, many trial items should be written related to each factor. More items than required should be written for each factor. Let's write some trial items for the factors given above:

Trial items for the factor of teaching:
I believe that I acquire more information than necessary in class
Students giving correct answers are rewarded in class,
Teacher threatens the students with grade
When students make some errors, they are corrected gently
The course content prepares me for the real life
I think that the course content is considerably intense and unnecessary
…

Trial items related to classroom environment:
Teacher is only interested in successful students.
I have a good communication with my classmates
I can comfortably share my problems with my classmates
I feel lonely in class
I cannot communicate with my teacher
Physical conditions in class are good
I do not feel bored in class
I wish I were in another class
…

Trial questions written in relation to teaching and classroom environment should be reviewed according to item writing criteria partly explained below before piloting. In this connection, when the items written in relation to teaching factor are examined, it is seen that some modifications can be made. For example, though the items written seem to be within the framework of teaching factor, they can be criticized and restated as follows:

> 'I believe that I acquire more information than necessary in class', in this item, what does the word more mean? I think the item is not clear enough to understand. Moreover, the uncertainty whether this item should be evaluated as negative of positive may yield some problems in its scoring. The items 'Students giving correct answers are rewarded in class' and 'When students make some errors, they are corrected gently' can be related to another sub-factor such as giving feedback. The item 'Teacher threatens the students with grade' can be an item related to classroom management. In addition, the items 'The course content prepares me for the real life' and 'I think that the course content is considerably intense and unnecessary' are items which can be under the heading of content.

The following criticisms can be directed to the items written for the classroom environment factor.

> The item 'Teacher is only interested in successful students' seems to be not very clear and understandable. On the other hand, the items 'I wish I were in another class', 'I cannot communicate with my teacher' and 'I feel lonely in class' are not clear and difficult to comprehend. The item 'physical conditions of class are good' is related to the physical aspect of the classroom

but it would have been better if more items can be included to assess this aspect.

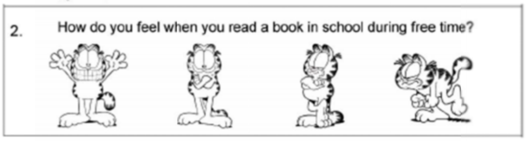
Some Rules to Be Followed While Writing Items

Although there are no certain rules to be followed while constructing items, for higher quality items to be written, the number of the trial items should be three times more than the number of the actual items to be included in the target test. Some of the rules to be followed while writing items can be as follows (Berg, 2007; May, 1997; Sarantakos, 1998; Şeker & Gençdoğan, 2006):

– The words in the items should be focused on what is to be measured
– Only one thing should be measured with one item
– Language must be simple, clear.
– Items should be written according to grammar rules of the given language and punctuation and writing mistakes should not be committed.
– Questions are not too general or insufficiently specific.
– Avoid using prejudicial language.
– Avoid ambiguity; that is, using words with several different meanings, double negatives.
– Avoid double-barreled and complex question.
– Avoid affectively worded questions.
– Words such as all, always, no more, never only, exactly, almost should be avoided.

Scaling

Determining the number of options and words to be used in the statements is of great importance. For example, no difference can be seen between the options 'Strongly agree' and 'Agree' because both of them indicate an agreement with something. When a large number of items are written, some options without much difference in their meaning may have to be used. For example, it is very difficult to differentiate among the options 'sometimes', 'occasionally', 'sparsely', 'rarely', 'very little'. This is of greater importance for the test administered to younger age groups. Through sample instructions, this problem can be reduced. Moreover, some issues should be taken into considerations in pilot applications. These are: recording of test beginning time, investigation of the reason for any item which is not clearly understandable throughout the testing process, if feedback about the non-comprehensibility of a test item is taken from more than one participant, then the reason behind this should be investigated. In addition, evidence can be collected for the suitability of the scale for the developmental level of the target population in piloting applications. The terms used in the scale aiming to test younger age groups can be supported with visuals. It is seen that this was considered in McKenna and Kear's (1990) 'elementary reading attitude' scale.



As a first stage of item selection, the test is administered to a small group. After this administration, which items should be kept and which items should be discarded from the test is decided. Then statistical analyses are decided. There is a need to score each test item according to their options. For example, in a five-point Likert type scale, when the option 'Strongly agree' is scored with 5, then the following options should be scored by subtracting 1 from the previous one as 'Agree' is scored with 4, 'Partially agree' with 3, 'Disagree' with 2 and 'Strongly disagree' with 1. Negative items are scored inversely. For example, if the option marked is 'Strongly agree', it is scored with 1 and if 'Strongly disagree' is marked, it is scored with 5. In order to be able to be used in test item correlations or reliability and validity works of the scale, total score taken by each participant is calculated.

Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) Usage in School Attitude Survey

The fact that school attitudes are affected by many factors has already been stated. Some factors which may not be taught initially may have some influences on attitudes towards school. For example, attitudes of family, attitudes of close circles, feeling belonging to school and teaching activities have influences on both attitudes towards school and academic achievement. In studies aiming to develop a scale to evaluate attitudes towards school, theoretical structures can be tested with EFA analysis to determine what factors are influential. In general, the studies related to attitudes towards school were carried out in such a way so as to analyze and explain the attitudes towards school through a single or few variables. None of these studies analyze the variables that affect all the attitudes towards school in unity. The EFA and CFA studies explain what variables affect the attitudes towards school and establish a model that shows the factors that are in harmony with each other.

By determining among which factors are there strong relations, EFA analyses help to determine the factors to be included in a scale. CFA analyses look for the causality relations among the determined factors. CFA analyses have been widely used in test development process followed in social science research in the last decade. CFA is just one type of factor analyses. This analysis is used to determine whether the construct structured by the researcher is consistent and suitable and reveal causality relationships. It tests the model constructed by the researcher. The stages of making up a CFA analysis are as follows:

Conduct EFA analyses

⇩

Determine the factors- Determine the constructs in the test

⇩

Develop the hypothesis (Determine how many factors which are influential)

⇩

Create the correlation web among the factors (determine their relationships with each other)

⇩

Develop the model to be tested

⇩

Check the fitness of the suggested model with fitness indexes

⇩

Decide whether the model is suitable or not

EFA Analyses

During the process of developing a measurement instrument, before conducting CFA analyses, items of the measurement scale should be determined with EFA analyses. During these analyses, the number of the items may be reduced and related items can be converted into one item. If possible, factors in EFA analyses should be tested in different samplings. When it is difficult to reach different samplings, by making use of statistical program packages, the consistency of the results of EFA analyses should be tested on another sampling randomly selected from the sampling of the study.

Factor analysis enables us to assess the ‘factorial validity’ of the questions which make up our scales by telling us the extent to which they seem to be measuring the same concepts or variables (Bryman & Cramer, 2006, p. 324). Exploratory factor analysis is concerned with whether the covariance or correlations between a set of observed variables can be explained in terms of a smaller number of unobservable constructs known either as latent variables or common factors (Landau & Everitt, 2004). Exploratory factor analysis is often used to gather information about (explore) the inter-relationship among the set variables.

A first step is to perform a factor analysis in order to assess the suitability of data for factor analysis. This involves inspecting the correlation matrix for coefficient of .30 and above and then calculating the measure of sampling adequacy (KMO) and Barletts' test of sphericity.

The second step involves the determination of the underlying factors in the set of variables. Principle components analysis PCA attempts to produce a smaller number of linear combinations of the original variables in such a manner that most of the variations in the pattern of correlations are captured (Palland, 2002). PCA is a multivariate technique for transforming a set of related (correlated) variables into a set of unrelated (uncorrelated) variables that account for decreasing proportions of the variation in the original observations. PCA is essentially a method of data reduction that aims to produce a small number of derived variables that can be used in place of the larger number of original variables to simplify subsequent analysis of the data (Landau & Everitt, 2004). Factor analysis can determine the degree to which they can be reduced to a smaller set (Bryman & Cramer, 2006).

Stating that factors analyses are carried out to convert different items related to the same concept into one item, Bryman and Cramer (2005) argue that through them, factorial validity of the items is determined. In addition to this, EFA factor analysis aims to reduce high number of items to more manageable number. That is, it can be used to reduce the constructs. Through EFA factor analysis, a large number of variables or concepts can be brought together and so they can be assigned common meanings. For instance, let's assume that the following questions are taught to represent the factors related to close circles and family believed to influence attitudes towards school.

– Negative attitudes of my close circles and family towards school discourage me,
– I want my family to be informed about may school works,
– My family thinks that my going to school is unnecessary,
– My family supports my preference for the school,
– My family supports my school works …

When all the above-given items are thought to be included in the same factor as a result of EFA factor, these five items can be explained within only one supra-concept. In determining what this supra-concept can be, factor analysis may make a great contribution. For the above-mentioned items, the common factor or supra-concept can be 'involvement of the family in the process'. As a result of EFA factor analysis, many items seem to be related to one factor should be combined into a common concept or under an umbrella concept.

For example, when the following items included in a test developed to evaluate school attitudes (Şeker, 2011) are examined, it is seen that if these items were required to be combined into a common factor, the concept of 'reluctance' can be good alternative be included within the name of this factor.

– Communication within the family makes me feel less positive towards school.
– My family considers my going to school unnecessary.
– Negative attitudes of the people in my close circle towards school negatively affect my eagerness.
– My efforts are being overlooked and this decreases my interest to study.
– I feel as if I am out of the activities in most of the courses.

– I cannot participate in many courses.

Sometimes, it may be difficult to come up with a common concept just by looking at the test items developed to evaluate attitudes towards school. In such cases, opinions of experts and linguists can be sought.

Factor analyses are conducted to test the theoretical structures. A factor analysis shows how many different structures a test is made of. What is done with a factor analysis is to elicit the relationships within the items of a test. That is, factor analysis shows the correlations among the test items. Moreover, factor analysis is evidence used to verify the construct validity of a test (Dooley, 1995, p. 93). Factor analysis is a kind of factorial validity work.

The most widely used factor analysis is Principal component factor analysis (principle-axis factoring). There are some other different methods in SPSS such as alpha, image and maximum likelihood. Yet, as they produce less information, they are used less. The main difference of them with Principle component is that Principal component analyzes all the variances in variables; that is, it is assumed that the items in the test are faultless with perfect reliability.

There are two main criteria used to determine how many factors will be involved Bryman (2001, p. 267). One is looking at whether Kaiser' eigenvalue is higher than 1, and the second one is graphically looking at Scree. There are two methods of transforming factors; orthogonal (varimax) and oblique. Orthogonal conversion is used to distinguish among items which are not related to each other or independent of each other Bryman (2001, p. 268). Oblique conversion, on the other hand, shows among which factors are there correlations.

Through EFA analyses, factors in a test should be determined. For example, let's assume that the items suggested as a result of EFA analysis for a test developed to evaluate attitudes towards school are as given in Table 1. It can be seen in this table that the 22-item questionnaire aiming to elicit attitudes towards school consists of six factors. While reducing the items in the questionnaire, those component matrix items with load of 0.40 and over have been selected, and thus, they are made inter-correlations quite strong (Palland, 2002). In factor analysis, if some items just do not load on the components obtained, they are omitted and the analyses are repeated.

The following steps were taken in order to reduce the number of the questions in the questionnaire:

An inspection of the correlation matrix for evidence of coefficients greater than 0.3. If few correlations above this level are found, then factor analysis may not be appropriate. Items were eliminated if they did not have a loading of at least 0.30, a commonly used cutoff, with any one factor. In Walker and Fraser's (2005) and Johnson and Steven's (2001)'studies, the same method was used to eliminate the items.

Table 1. Suggested scale items

Scale items	Factor No.	Factor value for the 1st factor	Rotated value	Item scale correlation	Extraction
1. I share my learning problems easily.	1	0.357	0.621	0.389	0.483
2. Students are provided help in learning activities.	1	0.510	0.616	0.500	0.464
3. I do not feel bored with the lessons.	1	0.418	0.566	0.482	0.460
4. I feel lucky that I am a student of this school.	2	0.478	0.560	0.482	0.590
5. It is a privilege to study in this school	2	0.707	0.477	0.658	0.538
6. I adequately make use of the services given at school.	2	0.357	0.708	0.347	0.550
7. I wish I were a student of another school.	2	0.416	0.668	0.407	0.490
8. I feel lonely in the classroom.	3	0.464	0.626	0.443	0.448
9. I am not able to have a healthy communication with my teachers.	3	0.592	0.609	0.542	0.576
10. Teachers are only interested in hardworking students.	3	0.350	0.458	0.465	0.624
11. Opportunities for questioning and criticising are provided.	4	0.486	0.680	0.444	0.580
12. Students' mistakes are corrected without offending them.	4	0.535	0.661	0.511	0.578
13. Exams measure my real success.	4	0.488	0.589	0.484	0.465
14. Exam questions are clear and understandable.	4	0.714	0.454	0.680	0.592
15. Communication within the family makes me feel less positive towards school.	5	0.499	0.439	0.490	0.400
16. My family considers my going to school unnecessary.	5	0.482	0.643	0.471	0.525
17. Negative attitudes of the people in my close circle towards school negatively affect my eagerness.	5	0.565	0.595	0.544	0.505
18. My efforts are being overlooked and this decreases my interest to study.	5	0.538	0.577	0.502	0.516
19. I feel as if I am out of the activities in most of the courses.	5	0.426	0.441	0.429	0.414
20. I cannot participate in many courses.	5	0.265	0.775	0.311	0.633
21. I do not want to go to school	6	0.441	0.561	0.444	0.511
22. I do not feel that I belong to this school.	6	0.415	0.544	0.432	0.443

Note: These items were taken from Şeker (2011).

Another way of reducing the number of the items in the study is that if you find that some items just do not load on the components obtained, you may also need to consider removing them and repeating the analysis (Ntoumanis, 2001). The items were reduced in the questionnaire by extracting the questions thought to have different components.

Suitability of KMO sampling is connected with the suitability of the correlation among the questionnaire items. The value over 0.60 is an acceptable value (Ntoumanis, 2001, p. 140). If KMO value is high, Bartlett test becomes statistically significant. Both of them having these values demonstrates that factor analysis is applicable and the correlation among the items is really high (Ntoumanis, 2001, p. 142).

According to the findings presented in Table 1, it is seen that the 22-item questionnaire is made up of six factors. When the values in the first factor are examined, it can be decided whether the questionnaire can be used as a one-factor questionnaire or not. Moreover, it is seen that item-scale correlation values are high. This finding proves that each item of the test is related to what the test aims to evaluate.

According to Table 1, Student's attitudes towards school factors:

Factor 1: Teaching
Q1.
Q2.
Q3.

Factor 2: School image
Q4.
Q5.
Q6.
Q7.

Factor 3: Loneliness at school
Q8.
Q9.
Q10.

Factor 4: Testing and feedback
Q11.
Q12.
Q13.
Q14.

Factor 5: Reluctance
Q15.
Q16.
Q17.
Q18.
Q19.
Q20.

Factor 6: Belongingness
Q21.
Q22.

In the factor analysis, attitudes towards school were found to be related with these factors.

CFA Analysis. It is aimed to determine the level of the change taking place in unity of the components (above-mentioned factors) of students' attitudes towards school and to develop a model by determining the structure of the relations among these factors. In other words, the aim is to investigate whether the above-mentioned six factors together affect the attitudes towards school. At the end of the application, by examining the relations among the dimensions of the questionnaire, the factors that are in compliance with each other were determined through structural equation modeling (SEM).

Structural equation modeling (SEM) is used in order to test the multiple relations in the school attitude questionnaire. This technique is used to estimate, analyze, and test models that specify relationships among variables (Bruce, 2003). This technique is called confirmatory factor analysis and is a part of SEM (Daniel, 2004). SEM can be explained as a technique that helps the researcher to establish a model in order to find the relationships among variables that are observed in the studied sample (Ader, 2004). In SEM, a model is established at the beginning and this model is tested to see whether it is supported by the data obtained. If the model suggested is not in compliance with the data, the researcher redesigns the model and retests it by using the same data. For this reason, SEM studies are corrective and explanatory (Klaine, 1998).

SEM Analysis

Structural equation modeling can perhaps best be defined as a class of methodologies that seek to represent hypotheses about summary statistics derived from empirical measurements in terms of a smaller number of 'structural' parameters defined by a hypothesized underlying model (Kaplan, 2009, p. 1). A standard statistical technique for evaluating a measurement model is exploratory factor analysis (EFA). EFA is not generally considered a member of the SEM family. EFA does not require a priori hypothesis about how indicators are related to underlying factors or even the number of factors. Hence the term "exploratory," which in this context means that the researcher has little direct influence on the correspondence between indicators and factors (Kline, 2005, p. 71).

EFA factor analysis is used to elicit information about the nature of the factors determined by the researcher rather than to test a specific hypothesis. CFA (corrective factor analysis) is generally used to test a hypothesis developed in line with a theory. Usually, it is used after EFA analysis has been carried out. The main purpose of CFA analysis is to test whether a clearly delineated model is confirmed by data. Yet, confirmation of a model by the data does not mean that the model has been thoroughly justified. The researcher may assume that the given model is justifiable for other models (Şimşek, 2007, p. 4). Path analysis entails the use of multiple regressions in relation to explicitly formulated causal model.

Path analysis cannot establish causality; it cannot be used as a substitute for the researcher's views about the likely causal linkages among groups of variables. All it can do is to examine the pattern of relationship between variables, but it can neither confirm nor reject the hypothetical causal imagery (Bryman & Cramer, 2006, pp. 313-314). The relationships between observable variables and latent ones are shown with a path diagram. The relationships are described by parameters that indicate the magnitude of the effect (direct or indirect) that independent variables (either observed or latent) have on dependent variables (either observed or latent). Latent variables are hypothetical variables that cannot be observed directly (Hershberger, Marcoulides, & Parramore, 2003, p. 4).

Let's assume that attitudes towards school are latent variable. We have no chance to directly measure school attitudes. Then, assume that teaching, classroom environment, teacher, student, school rules, family and exams are observable variables and they are related to attitudes towards school. When the relationship between the observable and latent variables is assumed to be linear, a diagram similar to the following can be constructed:

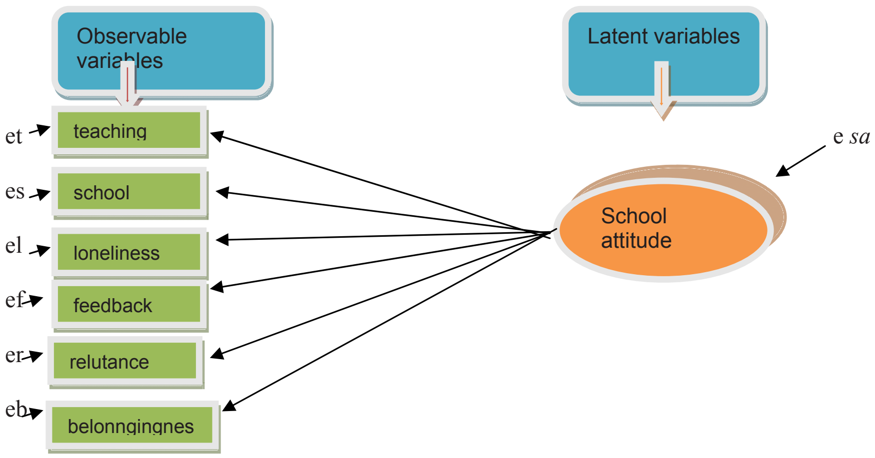


Chart 1. Hypothetical observable and latent variables related to school attitudes

Meaning of the symbols in Chart 1

	Latent variable
	Observed variable
	Recursive relation
	Measurement error in observed variable
	Disturbance error in Latent variable

SAMPLE SIZE

There is no consensus on the size of sample to be included in any study. The general consensus is that the bigger the size of the sample, the better it is. Garsuch argued that it should not be fewer than 100 (cited in Bryman, 2001, p. 263). A similar criterion is suggested by Ntoumianis (2001, p. 138). In general, samplings used in factor analysis research consist of 200 or more participants. SEM is still a large-sample technique. Because several factors affect sample size requirements in SEM, however, it is difficult to give a simple answer to the question of how large a sample needs to be. Some guidelines about absolute sample size in estimation methods were offered earlier (small, N < 100; medium, N between 100 and 200; large, N > 200). Another consideration is model complexity. A sample size of 200 or even much larger may be necessary for a very complicated path model. Although there are no absolute standards in the literature about the relation between sample size and path model complexity, the following recommendations are offered: a desirable goal is to have the ratio of the number of cases to the number of free parameters be 20:1; a 10:1 ratio, however, may be a more realistic target. Thus, a path model with 20 parameters should have a minimum sample size of 200 cases (Kline, 2005, p. 111).

GOODNESS FIT-INDEXES RELATED TO CFA STRUCTURE OF THE SCALE

There are different views with regard to the acceptability of Chi-square goodness test. For instance, according to different authors, the rate of Chi-square/freedom should be less than 3 (Alcı, 2007, p. 68), between 1 and 3 (Carmines & McIver, 1985, cited in Arbuckle, 2005, p. 493), and between 2 and 5 (Marsh & Hocevar, 1985, cited in Arbuckle, 2005, p. 493). The following are interpreted as good or perfect: CFI value close to 0.95, TLI value close to 0.95 and NFI value about 0.95 (Schumacker & Lomox, 2004, p. 82).

Applications suggest that the RMSEA value should be 0.05 or less, or 0.08 or less. It is very good if it is less than 0.05, and good and acceptable if it is less than 0.10 (Loehlin, 2004; cited in Arbuckle, 2005, p. 69). Browne and Cudeck (1993) suggested that 0.05of RMSEA indicates a close fit and that values up to 0.08 represent reasonable errors of approximation in the population (cited in Jöreskog & Sörbon, 1993). Steiger suggests that values below 0.10 indicate a good fit to the data and values below 0.05 a very good fit to the data (cited in Kelloway, 1998).

AGFI and GFI values close to 1 can be interpreted as good. Unfortunately, there is not a strict norm for these indices. As a rough guide, it is currently viewed that a model with a GFI or AGFI of 0.95 or above may well represent a reasonably good approximation of the data (Hu & Bentler, 1999, cited in Hershberger, Marcoulides, & Parramore, 2003, p. 19). The GFI ranges from 0 to 1, with values exceeding 0.9 indicating a good fit to the data (Kelloway, 1998).

Coefficients related to item-factor correlations calculated by confirmatory factor analysis are presented in Figure 3.

(X^2/sd) value calculated through the confirmatory factor analysis is 1.86 and this value shows that the suggested factor model fits well with the data collected. As a result of the analysis, GFI value was calculated to be .93, AGFI .95 and CFI .95, NFI .93, NNFI .94; RMR .06 and RMSEA .049; hence, it can be argued that six-factor structure of the scale is acceptable and can yield valid results. In addition, as can be seen in Figure 3, the observable data show good fit to six-dimensional model. Path coefficients vary between .37 and .67. All of these values are higher than .30 and according to Klein's (2005) values higher than .30 are good values. In the model shown in Figure 3, it is believed that the attitudes towards school depend on student's effort, loneliness of the student at school, his/her sense of belonging, feedback, image of school and teaching activities.

There is a need to conduct second order factor analysis to confirm whether school attitudes are made up of the combination of six factors; teaching, school image, loneliness, testing, reluctance, belongingness.

SECOND ORDER CONFIRMATORY FACTOR ANALYSIS

In addition to explanatory and confirmatory factor analyses conducted to test the construct validity of the scale, second order confirmatory factor analysis can be carried out through LISREL program to determine the extent to which six factors (teaching, school image, loneliness, testing, reluctance, and belongingness) indicate a good fit to the supra-structure, school attitude.

In the second order confirmatory factor analysis application, correlation matrix obtained from 6 factors is used as data.

As a result, the argument that school attitude consists of 6 factors; loneliness, image, reluctance, testing, teaching, belongingness, was supported. In addition to this finding, the coefficients revealed by second order confirmatory factor analysis relating to factor-scale relationships are presented in Figure 4.

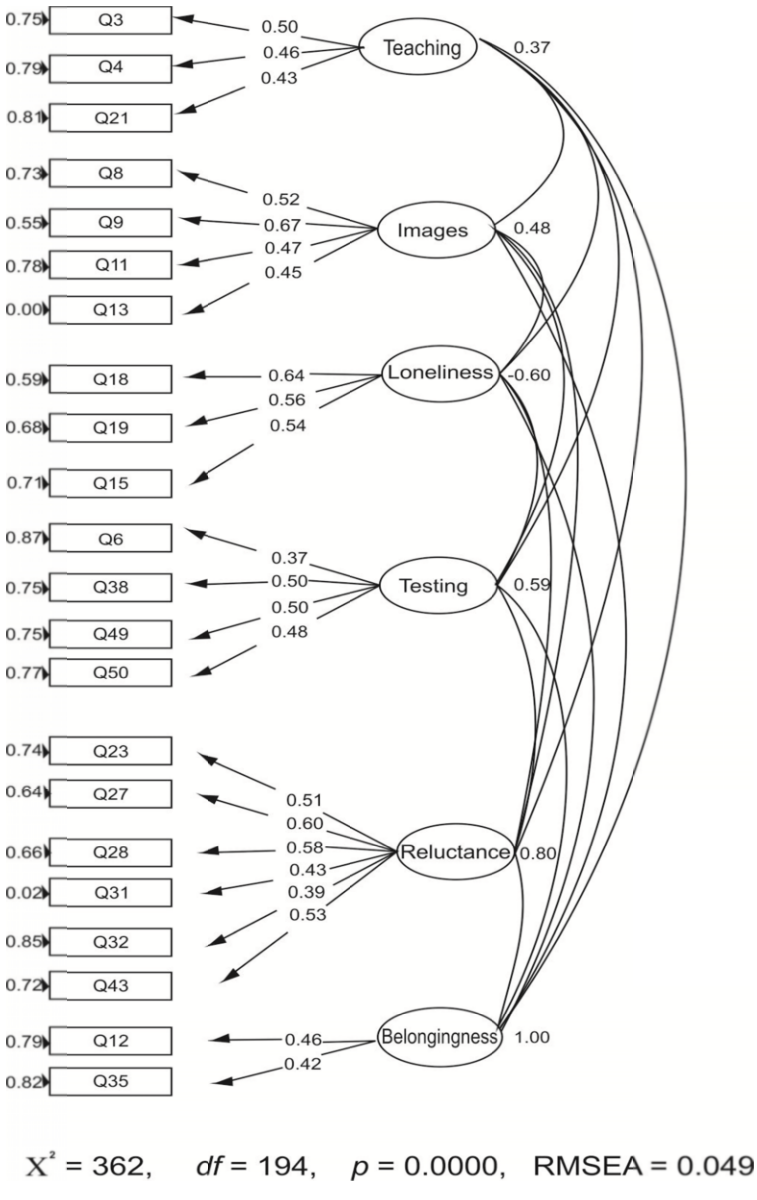


Figure 3. Item-factor correlations

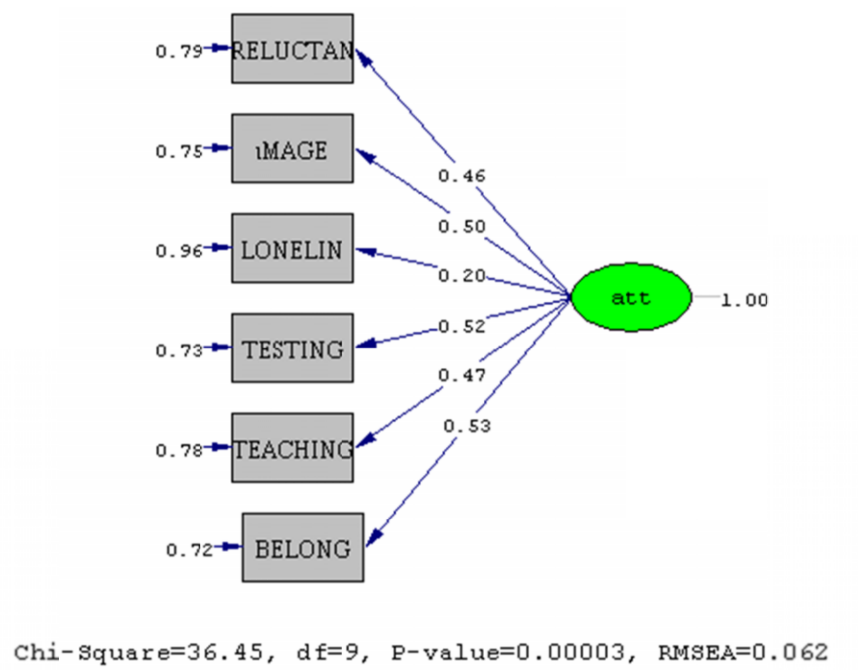


Figure 4. School attitude scale's factor-scale relationships

As can be seen in Figure 4, six-factor structure indicates a good fit to the attitude model. Path coefficients vary between .20 and .53. Except for the coefficient of loneliness, this value is higher than .30 for all the factors. (X^2/sd) ratio calculated with second order confirmatory factor analysis is 4.05 (p=.00) and this value shows that the model is in compliance with the actual data (Şimşek, 2007). As a result of second order confirmatory factor analysis, GFI value was calculated to be .98, AGFI .96 and CFI .97, NFI .97, NNFI .94; RMR .03 and RMSEA .06; hence, it can be argued that six-factor structure of the scale is acceptable and can yield valid results.

As a consequence, the questionnaire measuring the attitude towards school is comprehensive. The variables exist together in harmony, and they explain the important part of attitude towards school. However, the number of the items (questions) in the questionnaire can be increased by taking the variables in the questionnaire into consideration. Relationship ratios among the items and/or variables and compliance weighting may vary in a different application.

SOME CLOSING THOUGHT

School attitudes are believed to be related to in-school, out of-school and some other factor. School attitude, as a supra-concept, cannot be limited to learning environment of the school. School attitudes are affected by many variables such as learning environment, peer relations, academic achievement, belongingness, and extra-curricular activities. Therefore, some of the items included in the tests developed to evaluate any of these variables may have some similarities with the items included in any school attitude test. Hence, great care should be taken while determining the scope of the tests developed in social sciences. To what extent does the scale match with the "reality"? Even if, a perfect tool were developed, there would be many criticisms to be directed to it such as being distant from reality or not being able to reflect all the colors of reality. In order to reduce such criticisms or limitations, there are some steps to be taken. One of them is the effective use of data collection means to form the scope of the test. Methods used to reduce such limitations depend on effective use of many data collection tools ranging from literature review, interviews, and case studies to narrative strategies. Following data collection procedure, factors should be hypothetically determined in relation to test content and then trial items should be written for these factors. Here, while writing items, there are some rules to be followed and special attention should be paid to scoring. Then, EFA vs DFA analyses should be conducted. EFA analysis serves the function of determining among which factors there are strong relationships and in this way which factors should be included in the test and reducing items. With CFA analysis, causality relationships among the factors are sought. CFA analysis is one type of factor analyses. These analyses test whether the construct developed by the researcher is consistent or not and reveal causality relationships. By checking through the values obtained as a result of CFA analysis and suggested hypothetical model fitness indexes, it is decided whether the model is suitable or not.

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8. DEVELOPMENT OF GENERIC CAPABILITIES IN TEACHING AND LEARNING ENVIRONMENTS AT ASSOCIATE DEGREE LEVEL

INTRODUCTION

History of Associate Degrees in Hong Kong

In response to the demands imposed by the knowledge-based economy, Hong Kong underwent a relatively revolutionary change in its tertiary education scene in 2000, with the mission to increase the percentage of the population able to receive tertiary education from 30% to 60% within a decade (Hong Kong SAR, Education Commission, 2000). In this light, the American model of community colleges (awarding associate degrees) was imported to and pioneered in Hong Kong in 2000 by a reputable university (Lee & Young, 2003). Within two years, almost all of the other tertiary institutes had established their own subsidiaries, running in self-financed modes, to offer associate degree programs. The number of associate degree programs increased from 16 in the academic year 2001/2002 to 157 in 2011/2012, with a corresponding increase in the number of enrolled students from 3,732 to 27,822 (Hong Kong SAR, Information Portal for Accredited Post Secondary Programs, 2012).

The introduction of the associate degree award in Hong Kong follows the American model for mass education (Postiglione, 2009). In particular, the American tertiary education model can generally be seen as two-tiered, with government-funded or privately-funded universities remaining in the upper-tier and associate degrees in the second tier. Successful completion of an associate degree in the States provides seamless mobility to the upper-tier – direct entrance to the third year of a four-year degree award – where the choices of articulation pathway are also abundant. However, the situation is quite the contrary in Hong Kong, where almost all university places are government-funded, resulting in a restricted number of senior places being reserved for associate degree graduates (Heorn, 2006). As a result, there remains a huge gap between the demand and supply of government-funded university places. Critics worry that the associate degree will become an award that leads nowhere, neither sufficing for vocational purposes nor for further academic pursuits (Kember, 2010).

The fact that the institutions offering associate degrees espouse visions and missions similar to those of the universities offering degrees – to prepare students with 21st century skills for pursuing life-long learning and leading the lives of responsible citizens in order to cope with the ever-evolving demands of the

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 169–184.

workplace and society in general. Their efforts in such endeavors have often been overshadowed by the issue of articulation, which is taken as the only goal of the associate degree. Therefore, much of the public discussion and research has been conducted to examine the introduction of the associate degree in Hong Kong, from both administrative and policy perspectives, so as to address the 'shortage' issues in articulation places. On the other hand, the question of whether this new tier of education has helped students to develop generic capabilities has largely been overlooked.

Twenty-first century skills, such as problem-solving, reasoning, systemic thinking, and interpersonal skills, are often generic and tacit in nature and such require distributed learning (Bransford, Brown, & Cocking, 2000; Sawyer, 2006). Their development may require an orchestrated and coherent learning environment at program level instead of teaching of the 'right' subject content in a single course. However, only scant effort has been made so far to understand students' psychological facets and the educational facets of the learning environment on the mechanisms for developing generic capabilities in associate degree students. With the development of the associate degree in Hong Kong now having completed its first decade, it is high time to undertake an empirical study to unravel the issues.

Characteristics of Associate Degree Students, Teachers and the Learning Environment

As argued by Resnick (2010), educational changes and classroom innovations are complex and hence it is useful to understand the learning environment as a multi-layer interactive ecological system. The multi-layer system involves macro-, meso- and micro-level factors that pertain to change in the educational change or contexts. The learning environment in the associate degree programmes in Hong Kong can also be described and understood using this three-layer interactive ecological system. The history of the associate degree in Hong Kong, as portrayed in the introductory paragraph, provides the macro-level backdrop regarding the scene we have been facing in the tertiary sector during 2000 and onwards. Meso-level issues in the system involve institutional climate, ethos and practices in teaching and learning; while micro-level issues involve the psychology of human factors, both teachers' and students', that affect the teaching and learning processes in the classroom. This section describes both meso-level and micro-issues, with all of these factors nested within the macro-level context of change. It is believed that the mechanism of the learning and teaching environment nurturing students' generic capabilities at associate degree level results from the interplay of all these factors at different levels in this ecological system of change.

Meso-level: Strong ethos in teaching and learning. Most of the associate degree programs are offered by institutions run by local universities, and therefore they employ quality assurance processes, administrative procedures, curriculum design and modes of study that are like those of their parent institutions. Despite these marked similarities in the procedural and administrative matters, there are some key differences in terms of their overall institutional climates and ethos of teaching and learning, and funding modes of the institutions that make these two tiers different from each other.

Almost all of the institutions offering associate degrees are self-financed, and hence most of the institutional income relies on the student in-take in each academic year. It is very crucial for the institutions to make competitive 'marketing' plans to ensure good enrolment rates. Moreover, from market responses and graduates' comments, it seems that a high articulation rate is one of the most critical determinants of the applicant's choice of institution. As a result, achieving a good articulation rate becomes the key agenda for institutions offering associate degrees. Benchmarking the success of a program based on the articulation rate may shape both teachers and learners' beliefs about what constitute good learning, good teaching and a good learning environment. This may lead to a high emphasis on the teacher's role in the teaching and learning process, in particular the design of assessment tasks and the need to teach for sufficient understanding to enable the students to meet the assessment requirements in order to get good grades for articulation. On the contrary, the capabilities that are not directly relevant to academic performance may be less valued, or overlooked, by both teachers and students.

Micro level: Students' and teachers' emphasis on academic performance. Undergraduates and associate degree students may differ from each other in some important presage characteristics that are relevant to understanding their learning experience and outcomes (Biggs, 1996). First, as discussed by Lee (1996), Hong Kong students are characterized by their strong examination orientation and, given the aforementioned competitiveness of articulation, associate degree students may manifest this to a new height. Fierce competition among peers and strategic use of tactics (for example, rote learning from lesson summaries, drilling on past exam papers) to excel in examinations are common among associate degree students. On the contrary, engagement in social relationships, participation in co-curricular activities, and breeding a sense of belonging to college life in general are of lesser concern to them (Lee, 2004). It is therefore expected that facets of peer relationships may exert less influence on the development of students' generic capabilities when compared to other facets that have direct bearing on teaching and learning.

Second, from veteran teachers' observations, associate degree students in general have lower self-esteem than their undergraduate counterparts, as a result of their head-on failure in the public examination (Lee, 2004). Even when associate degree graduates have re-entered university, many still manifest low self-esteem and consider themselves as less capable than their classmates who have followed a 'neat and normal' path to university (through the Joint University Program Admission System).

Unlike conventional local government-financed tertiary institutions, those offering associate degrees are mainly teaching institutions, focusing mainly on the provision of quality teaching. Most of the assigned duties of academic staff members in these institutions are teaching-related, and research activities are often made optional. As a result, teaching performance may factor in as one of the very important criteria for personnel matters (including recruitment, promotion and performance appraisal), and this leads to a very strong ethos among academic staff members to strive for excellence in teaching. Furthermore, this ethos is reinforced by elaborate quality assurance processes including minimum numbers and types of assessment tasks used, types of examination questions designed, annual peer class review exercises, pledge of return dates for assignments with feedback, and opportunities for students to review examination scripts for feedback purposes. All of these college-wide practices prepare academic staff members to become fluent in dialogue relating to learning and teaching matters. It is therefore expected that such fluency will translate into the design of learning and teaching environments that are conducive to students' articulation to other universities.

Learning Environment and the Development of Generic Capabilities among University Students

There has been a prevalence of research examining and tracking the development of college students' generic competences in the light of their college experiences (see for example Tinto, 1987; Pascarella & Terenzini, 2006). This strand of research has suggested that the overall college climate pertaining to both the academic and social aspects of students' lives are pivotal determinants of persistence and success (Tinto, 1975, 1987). Nevertheless, it has been argued that this research may not help to identify specific aspects of the learning environment that effect changes in students' generic capabilities. When universities are unaware of the underlying mechanisms, the development of specific capabilities to their full potential is less likely (Kember & Leung, 2005a, 2005b).

In this light, Kember and colleagues (Kember & Leung, 2005a, 2005b, 2009, 2011; Kember, Leung, & Ma, 2007) pioneered research work in characterizing important facets of the learning environment and students' perceptions of their generic capabilities with the use of a diagnostic instrument, the Student Engagement Questionnaire (SEQ; Kember & Leung, 2005b, 2009). Furthermore, they theorized and tested causal models of the impact of identified facets of the learning environment upon the development of generic capabilities (Kember & Leung, 2009, 2011). The Student Engagement Questionnaire consists of a total of 15 dimensions, six of which measure elements of the learning and teaching environment while the remaining nine measure generic capabilities that are important for lifelong learning. Kember and colleagues theorized that the six learning and teaching dimensions can be subsumed under three latent variables, namely 1) Teaching, 2) Teacher-Student Relationship and 3) Student-Student

Relationship; while the nine generic capabilities dimensions are grouped under two latent constructs of 1) Intellectual Capabilities and 2) Working Together.

The model developed by Kember and Leung in 2009 (the 2009 Model), using a sample of undergraduates in Hong Kong, hypothesized that (1) Teaching has a direct effect on the development of Intellectual capabilities while (2) Student-Student Relationship has a direct impact on Working Together, which in turn has a direct impact on Intellectual Capabilities. All three constructs in the learning and teaching environment domain (Teaching, Teacher-Student Relationship and Student-Student Relationship) inter-correlated with each other. Later in 2011, Kember and Leung revised their model by adding a direct path from Teaching to Working Together, and allowed the two capability latent variables, Working Together and Intellectual, to impact on each other (a covariance between the two latent variables) instead of Working Together impacting on Intellectual (Kember & Leung, 2011; the 2011 Model). Empirical data supported the hypothesized models and they have been replicated with different samples of Hong Kong graduates and undergraduate students. This converging line of findings suggests the adequacy and stability of the models in capturing the mechanism of developing generic capabilities in relation to learning and teaching environments in the Hong Kong tertiary context.

The Present Study

The objective of the present study was to examine the development of associate degree students' generic capabilities in relation to the learning and teaching environment. Specifically, we tested whether the mechanism of the impact of the teaching and learning environment on capability development identified for undergraduate students can be generalized to a sample of associate degree students. We believed the mechanism would be similar for the associate degree students but expected that there may be nuanced differences in the interplay of the learning and teaching environment and the development of their generic capabilities when compared to their undergraduate counterparts, due to the differences found in a complex multilayer ecological system. It was hoped that the results generated from the present study would shed light on the understanding of learning environments at the associate degree level and inform the design of learning environments that promote deep learning.

METHOD

Sample and Procedure

The target population in the study was all of the 1166 associate degree students enrolled in the Marketing, Engineering and Sociology programs of a community college in 2008 to 2010 in Hong Kong. The students were invited to complete a questionnaire in class at the commencement of the academic years of 2008, 2009 and 2010. The project research assistant explained the purpose of the study, the voluntary nature of the participation, the guarantee of confidentiality, and that all the results would be disseminated in aggregated formats. A total of 1110 students participated in the study voluntarily and completed the questionnaires, resulting in an overall response rate of 95.2%. Their ages ranged from 19 to 22.

Instrument

The questionnaire in this study was adapted from the Student Engagement Questionnaire developed to seek feedback from university students (Kember & Leung, 2009). This instrument consists of 33 items measuring students' perceptions of their generic capability development and elements in the teaching and learning environment. The original SEQ was developed through a series of studies (Kember & Leung, 2005a, 2005b, 2009, 2011) and, in its final version, the six generic capabilities include (1) *critical thinking*, (2) *self-managed learning*, (3) *adaptability*, (4) *problem solving*, (5) *communication skills*, and (6) *interpersonal skills and groupwork*. Previous studies had surveyed both graduates (Kember & Leung, 2005) and undergraduates (Kember & Leung, 2005b, 2009, 2011; Leung & Kember, 2005a). It was believed that the six capabilities in the instrument should also be applicable to associate degree students, and hence no change was made to the capability domain of the instrument.

The scales in the teaching and learning environment domain were modified in order to better characterize the relevant nature of the teaching and learning environment in the associate degree context. The original SEQ includes the following nine elements in the teaching and learning environment domain: (1) *active learning*, (2) *teaching for understanding*, (3) *feedback to assist learning*, (4) *assessment*, (5) *teacher-student interaction*, (6) *assistance from teaching staff*, (7) *relationship with other students*, (8) *cooperative learning*, and (9) *coherence of curriculum*. Three elements in this domain, *cooperative learning, coherence of curriculum,* and *assistance from teaching staff,* were dropped from the current study due to its relevance to the present context of associate degree programs as well as the length of the questionnaire. Since much of the curriculum space of the associate degree program is concerned with the provision of general education, the structure and coherence of the specific domain knowledge may not be salient to students. The remaining six elements were retained in the teaching and learning environment domain, which was believed to reflect the forms of teaching and learning at the associate degree level, which appears to make it suitable for the present study.

Appendix 1 displays the modified version of the questionnaire, with 25 items measuring the development of the six capabilities and the six elements in the teaching and learning environment. All the 12 scales have two items except *assessment* which has three. The items were rated on a 5-point Likert scale ranging from 1 (very little) to 5 (very much).

Thus, the 2009 and 2011 Models developed by Kember and Leung (2009, 2011) were modified according to the changes in SEQ, and the two models being tested in the present study are shown in Figure 1. The modifications to the original models were that: (1) the Student-Student Relationship latent variable was replaced by the observed variable *student-student interaction,* while *coherence of curriculum* of the Teaching latent variable and *assistance from teaching staff* of the Teacher-Student Relationship latent variable were dropped.

In the following section, we present the measure of internal consistency by computing Cronbach's alpha value using SPSS19.0 for the constructs under each of the five latent variables which were included in the model testing.

Teaching. Seven items were used to measure student's perception of the teaching they received inside the classroom. These items were grouped into three constructs – active learning (α = 0.529), teaching for understanding (α = 0.606), and assessment (α = 0.558).

Teacher-student relationship. Teacher-student relationship was measured by four items comprising two constructs to reflect students' perceptions of their relationship with their teachers, that is, feedback to assist learning from their teaching staff (α = 0.604), and teacher/student interaction (α = 0.598).

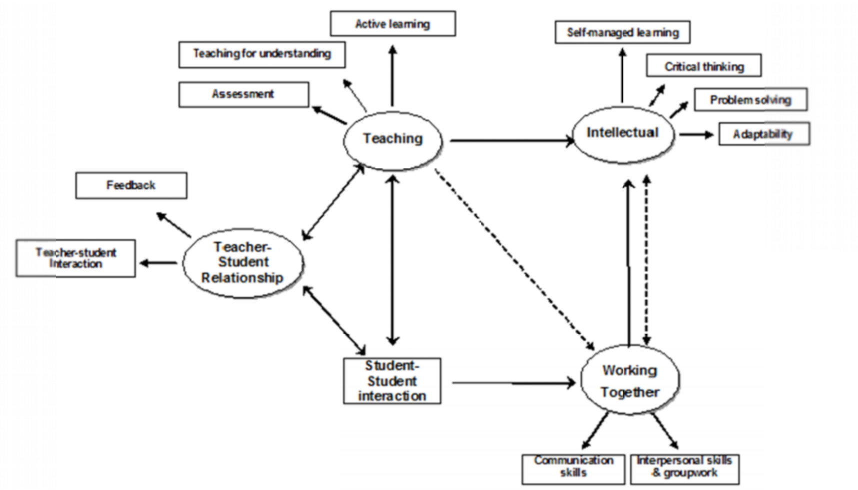

Figure 1. The modified hypothesised model relating the teaching and learning environment and development of generic attributes for associate degree students. Note: The 2009 Model without the dashed direct paths and the 2011 Model with the dashed direct path from Teaching to Working Together and the path from Working Together to Intellectual replaced by the dashed covariance path

Student-student relationship. There was only one construct with two items used to assess students' perceptions of their relationship with fellow students, which was student/student interaction (α = 0.462).

Intellectual. Eight items were used to assess the development of students' intellectual attributes. These items were grouped into four constructs: critical thinking (α = 0.586), self-managed learning (α = 0.676), adaptability (α = 0.50), and problem solving skills (α = 0.717).

Working together. Students' perception of the development in capabilities in communication and team work skills were measured by four items which were grouped into two constructs of communication skills (α = 0.680), and interpersonal skills & group-work (α = 0.498).

Mean scores for the scales were then computed by averaging their corresponding items and are shown in Table 1.

Table 1. Mean and standard deviation of the 12 subscales in the modified Student Engagement Questionnaire for associate degree students (n = 1110)

Dimension	Mean (SD)
Critical thinking	3.60 (0.57)
Adaptability	3.61 (0.58)
Self-managed learning	3.70 (0.69)
Problem-solving	3.37 (0.61)
Communication skills	3.51 (0.69)
Interpersonal skills and group work	3.74 (0.64)
Active learning	3.63 (0.57)
Teaching for understanding	3.75 (0.54)
Feedback to assist learning	3.66 (0.58)
Assessment	3.70 (0.48)
Relationship between teachers and students	3.90 (0.56)
Relationship with other students	3.59 (0.64)

Data Analysis

Structural equation modelling (SEM) was used to test the two hypothesised models. The aim was to replicate and then compare the two possible models developed for undergraduate students, as reported by Kember and Leung (2009) and Kember and Leung (2011), in the associate degree context with the adaption in the instrument. The two unstandardized factor loadings of *critical thinking* from Intellectual and *communication skills* from Working Together, and the variances of the two latent variables in the teaching and learning environment domain, Teaching and Teacher-Student Relationship, were fixed to 1 for identification purposes (Byrne, 2006).

The assessment of the model fit was based on several fit indexes including the root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), the standardized root mean squared residual (SRMR; Bentler, 2006) and the comparative fit index (CFI; Bentler, 1990). As a rule of thumb, a model with RMSEA < 0.08, SRMR < 0.08 and CFI > 0.90 would be considered as an acceptable fit to the data (Hoyle, 1995) and not rejected. Comparison of the two hypothesized structural models was made using the corrected Satorra–Bentler robust chi-square difference (ΔR-χ^2) test between the more stringent model (2009 Model) and the less stringent one (2011 Model) (Satorra & Benlter, 2001). We said the 2011 Model provided a statistically better fit than the 2009 Model if the ΔR-χ^2 test was statistically significant, that is, the path from Teaching to Working Together was statistically different from zero, and the relationship between Intellectual and Working Together is bi-directional, instead of uni-directional from Working Together to Intellectual.

We first checked the normality of univariate and multivariate distributions of the 12 measured constructs. The univariate distributions of the variables were only slightly non-normal (skewness: -0.66 to 1.13; kutosis: 0.48 to 0.69) but the normalized value (26.10) is large, which is indicative of the non-normality of the data (Benter, 2006; Byrne, 2006). Thus, the maximum likelihood procedure with the Satorra-Bentler robust correction (Satorra & Benlter, 1988, 1994) was used in the parameter estimations in SEM to adjust for non-normality. All the models were tested using the EQS package (Benlter, 2006). Converged solutions with no-of-range parameter estimates were obtained in all the analyses.

RESULTS

The 2009 Model

The covariance matrix of the 12 constructs was submitted for analysis (Table 3). All the factor loadings, variances of the latent variables and covariances between the latent variables, and the structural paths from the teaching and learning domain to the capability development domain in the 2009 Model, were statistically significant. The goodness-of-fit indices obtained for the model were R-χ^2 (df) = 304.05 (49), SRMR = 0.087, R-CFI = 0.925, R-RMSEA (90% CI) = 0.069 (0.061, 0.076), which yielded a reasonable approximation to the data. Figure 2 shows the standardized parameter estimates of the 2009 Model. All the standardized factor loadings were > 0.4. The three variables in the teaching and learning environment domain were positively correlated to a moderate to strong extent, as anticipated. The impacts of Teaching on Intellectual and of *student-student interaction* on

Working Together were small, while the impact of Working Together on Intellectual was strong.

Table 2. Covariance matrix of the 12 subscales in the analysis (n = 1110)

	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12
Critical thinking (v1)	0.330											
Adaptability (v2)	0.204	0.336										
Self-managed learning (v3)	0.174	0.187	0.473									
Problem solving (v4)	0.194	0.189	0.200	0.375								
Communication skills (v5)	0.159	0.182	0.237	0.206	0.472							
Interpersonal skills & groupwork (v6)	0.168	0.211	0.234	0.161	0.275	0.416						
Active learning (v7)	0.051	0.067	0.091	0.081	0.081	0.077	0.324					
Teaching for understanding (v8)	0.065	0.078	0.115	0.077	0.070	0.075	0.142	0.295				
Feedback to assist learning (v9)	0.072	0.092	0.114	0.105	0.088	0.085	0.138	0.162	0.331			
Assessment (v10)	0.058	0.062	0.084	0.064	0.058	0.075	0.080	0.086	0.089	0.231		
Teacher-student interaction (v11)	0.088	0.097	0.118	0.091	0.094	0.101	0.119	0.135	0.155	0.085	0.312	
Student-student interaction (v12)	0.040	0.073	0.095	0.063	0.085	0.101	0.110	0.080	0.100	0.090	0.116	0.405

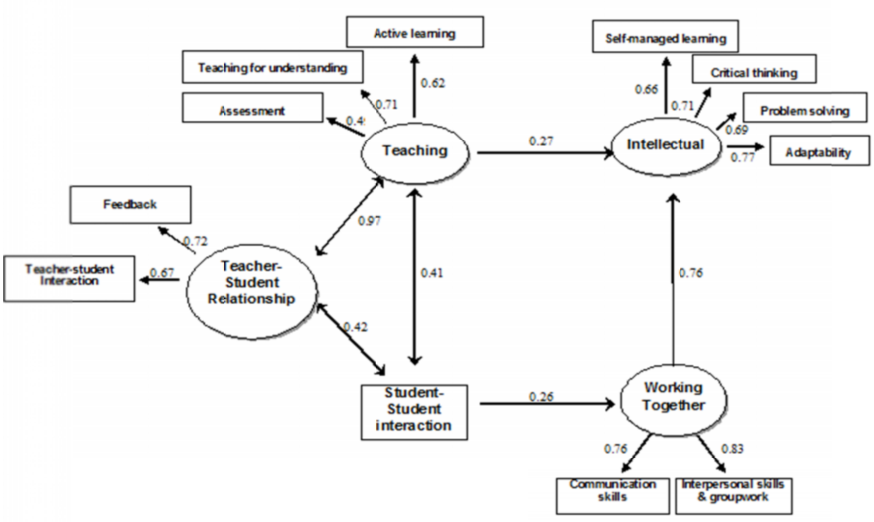

Figure 2. Standardised parameter estimates of the structural model relating the teaching and learning environment to the development of generic capabilities in associate degree students: The 2009 Model (n = 1110)

The 2011 Model

The fit indexes of the 2011 Model indicated an acceptable fit to the data with R-χ^2 (df) = 220.94 (48), SRMR = 0.038, R-CFI = 0.949, R-RMSEA (90% CI) = 0.057 (0.049, 0.065). All the factor loadings, variances of the latent variables and covariances between the latent variables, and the structural paths from the teaching and learning domain to the capability development domain in the 2011 Model were statistically significant. The $\Delta R\text{-}\chi^2$ test revealed that the less stringent 2011 Model provided a statistically better fit than the more stringent 2009 Model ($\Delta R\text{-}\chi^2$ = 129.67, df = 1, p-value < 0.001). The standardized parameter estimates of the 2011 model are shown in Figure 3. All the standardized factor loadings, the correlations among Teaching, Teacher-Student Relationship and *student-student interaction* in the teaching and learning environment domain and the path from Working Together to Intellectual in the capability domain in the 2011 Model remained similar to those obtained in the 2009 Model. In the 2011 Model, however, the impact of Teaching to Intellectual was estimated to be stronger while the impact of *student-student interaction* to Working Together was weaker when compared to the 2009 Model, after adding the path from Teaching to Working Together, of which the impact was estimated to be moderate.

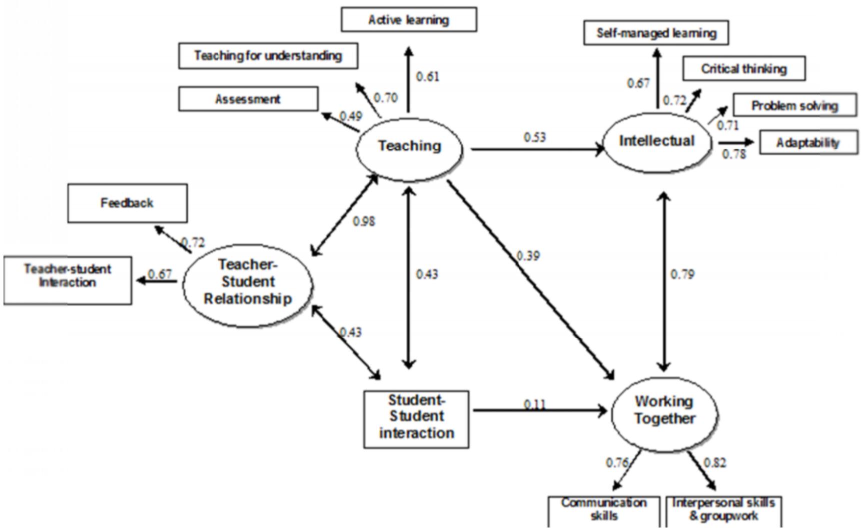

Figure 3. Standardised parameter estimates of the structural model relating the teaching and learning environment to the development of generic capabilities in associate degree students: The 2011 Model (n = 1110)

DISCUSSION

The results suggest that the development of generic capabilities in an associate degree learning environment follows a *similar* mechanism as found in an undergraduate learning environment; but there are some nuanced differences observed in the specific paths among variables. Comparison of fit of two hypothesized models suggests the 2011 Model is deemed more appropriate for characterizing the mechanism of various learning environment facets impacting on various facets of generic capabilities. Specifically, the 2011 Model demonstrates that the latent variable Teaching yields significant direct paths on both the latent variable of Intellectual and Working Together. Moreover, Teaching also yields an indirect impact on the nurturance of Intellectual through Working Together indirectly.

Taking a closer look at the fitted model, it can be seen that the magnitude of the coefficient of Teaching on Intellectual is relatively high (beta = 0.53), suggesting that indicators of assessment, teaching that focuses on understanding as well as the use of active pedagogies are salient for the development of intellectual capabilities (critical thinking, problem-solving, self-managed learning, and adaptability). At the same time, Teaching exerts influence on the nurturance of Working together (a cluster of generic social skills that includes communication skills, interpersonal and groupwork skills) but with a smaller magnitude (beta = 0.39) when compared to its path on Intellectual capabilities. In contrast, the role of the latent variable Student-Student interaction has a much weaker influence on the nurturance on Working Together (beta = 0.11) when compared to Teaching. In sum, in an associate degree level learning environment, much of the changes affected upon students are sourced from the formal learning processes (lectures and tutorials) and academic related activities.

Furthermore, the observed correlation between Teaching and Teacher-Student Relationship in the teaching and learning environment domain was quite different from previous studies in undergraduate samples. In the present study, the correlation was as high as 0.98, which was similar to the results of Kember and Leung's studies in 2005a and 2009, but was substantially higher than those reported in their later study (2011) (0.26-0.37). These findings may characterize teaching-oriented sub-degree tertiary institutions, where priorities and resources are placed on teaching and the provision of a caring culture. This may be because the academic staff members can be more accessible and more able to provide timely assistance to students outside regular weekly contact hours because their major responsibility is teaching and their duties are not mixed with research and community service. The high correlations between Teaching and Teacher-Student Relationship found in the current study and the two previous studies by Kember and Leung (2005a, 2009) might also have occurred because there were only two indicators used to characterize the Teacher-Student Relationship latent variable, which might not be good enough to separate the two distinct concepts of Teaching and Teacher-Student Relationships among associate degree and undergraduate students. Another reason might be the use of a mixture of students from the Marketing, Engineering and Sociology programs who might have responded differently to the modified SEQ. Indeed, Kember and Leung (2011) had reported disciplinary differences in the mechanism for how the teaching and learning environment affects the development of generic capabilities. Further studies should be conducted on the characterization of the elements in the teaching and learning environment in the associate degree context.

The pervasive role of the teacher in the associate degree learning environment on the development of students' capabilities is clear: teachers' practices in the classroom yield a direct influence on the development of both types of generic capabilities in students; and teachers' out-of-class interactions and feedback provided for students feed substantially into the process of learning and teaching in classroom. In this light, it is important for institutions offering associate degrees to foster good teaching and learning ethos and practices among teaching staff members (as the construct of Teaching is indicated by aspect of assessment, use of pedagogy, teaching for understanding as well as design of curriculum). Specifically, at the meso-level, the institute can maintain its existing quality assurance practices so as to benchmark quality teaching. Furthermore, it may be useful to introduce quality enhancement efforts to support academic staff members to develop their assessment and pedagogy literacy. By providing academic staff members with the theory of constructive alignment (Biggs, 1996), practices of cutting-edge assessment techniques and pedagogies, they can have both the principles and strategies to design curriculum, assessment and classroom activities to create a positive backwash effect in order to harness the students' examination-oriented mindset (Biggs & Tang, 2011). This would also be useful to provide the skills and tangible support for academic staff members to conduct action research, so that their practices can be both reflective and evidence-based. However, it is noted that this work was conducted in one of the associate degree institutions in Hong Kong, hence some of the meso-contextual factors described in the present study might be idiosyncratic to this institute and may not be representative to all other providers in Hong Kong. Further efforts should be made to replicate the current findings and examine in more depth the actual mechanisms of change in other similar institutions.

CONCLUSION

The present study examined the mechanism for developing generic capabilities in an associate degree learning environment. Despite the differences at the meso and micro levels when comparing associate degree and degree offering institutes, it was found that the mechanism for developing generic capabilities in associate degree students is similar to that found in undergraduate students. At associate degree level, the role of the formal curriculum, pedagogies and assessment that constitute the construct of Teaching in the model play a pivotal role in influencing the development of both the intellectual and social aspects of generic capabilities. In this light, it is suggested that there is a need to promote quality enhancement in learning and teaching among teaching staff members, so as to provide them with sufficient understanding, relevant theories and up-to-date, cutting-edge techniques in assessment and pedagogy.

Finally, after a decade, the development of associate degree in Hong Kong has already moved beyond its gestation period. Systematic empirical effort may also be needed to advance our understanding beyond the societal and policy levels to the classroom level. It is hoped that, through such systemic effort among practitioners, the existence of the associate degree in Hong Kong will become more than only a second chance for students to get into University, but will also add value to youngsters' generic competencies and prepare them for future pursuits of any kind.

APPENDIX 1

The Modified Version of the Student Engagement Questionnaire for Associate Degree Students

Critical Thinking:

1. I have the ability to make judgments about alternative perspectives.
2. I am willing to consider different points of view.

Self-managed Learning:

3. I feel that I can take responsibility for my own learning.
4. I am confident of my ability to pursue further learning.

Adaptability:

5. During my time at the College, I have learnt how to be more adaptable.
6. I am willing to change my views and accept new ideas.

Problem-solving:

7. I have improved my ability to use knowledge to solve problems in my field of study.
8. I am able to bring information and different ideas together to solve problem.

Communication Skills:

9. I have the ability to communicate effectively with others.
10. In my time at the College, I have improved my ability to convey ideas.

Interpersonal Skills:

11. I am an effective team or group member.
12. I feel confident in dealing with a wide range of people.

Active Learning:

13. Our teaching staff use a variety of teaching methods.
14. Students are given the chance to participate in classes.

Teaching for Understanding:

15. The teaching staff try hard to help us understand the course material.
16. The course design helps students understand the course content.

Feedback to Assist Learning:

17. When I have difficulty with learning materials, I find the explanations provided by the teaching staff very useful.
18. There is sufficient feedback on activities and assignments to ensure that we learn from the work we do.

Assessment:

19. The programme use a variety of assessment methods.
20. To do well in assessment in this programme you need to have good analytical skills.
21. The assessment tested our understanding of key concepts in this programme.

Teacher-student Relationship:
22. The communication between teaching staff and students is good.
23. I find teaching staff helpful when asked questions.
Student-student Relationship:
24. I feel a strong sense of belonging to students in my programme.
25. I frequently work together with others in my programme.

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PART III

STRUCTURAL EQUATION MODELING IN EDUCATIONAL PRACTICE

GREGORY ARIEF D. LIEM AND ANDREW J. MARTIN

9. LATENT VARIABLE MODELING IN EDUCATIONAL PSYCHOLOGY: INSIGHTS FROM A MOTIVATION AND ENGAGEMENT RESEARCH PROGRAM

INTRODUCTION

The application of latent variable modeling in various areas of psychological research has dramatically grown in popularity over the past three decades (see e.g., Breckler, 1990; Hershberger, 2003; MacCallum & Austin, 2000; Tomarken & Waller, 2005; Tremblay & Gardner, 1996 for systematic reviews). This growth is also apparent in educational psychology research that primarily seeks to address a range of applied and policy related questions to promote educational outcomes. *Contemporary Educational Psychology*, for example, recently dedicated a special issue on applications of latent variable modeling in educational psychology research (Kulikowich & Hancock, 2007). In their commentary in this special issue, Marsh and Hau (2007) called for educational psychology researchers to emphasize and adopt methodological-substantive synergies; that is, to conduct research that harnesses and makes the best use of methodological advancements in addressing important substantive issues which otherwise could not be appropriately pursued without such advances. In this context, applications of latent variable modeling techniques have the capacity to answer this call. This is the case because latent variable modeling is considered a unique and powerful approach to representing and assessing hypothetical (unobservable) psycho-educational constructs (e.g., academic motivation, engagement, self-concept) commonly delved within educational psychology research. That is, in latent variable modeling, latent constructs are measured by multiple manifest (observable) indicators and are linked to multiple antecedents, multiple mediators and moderators, and multiple outcomes – the majority of which are hypothetical and latent constructs themselves. Thus, latent variable modeling is a cutting-edge statistical tool with tremendous potential to shed light on the complexity of inter-relationships of factors relevant to educational outcomes.

In the present chapter, we provide an overview of contemporary applications of latent variable modeling techniques (e.g., confirmatory factor analysis [CFA], structural equation modeling [SEM], multiple-indicator-multiple-cause modeling [MIMIC]), exploratory structural equation modeling [ESEM], multilevel CFA and SEM) in addressing applied and substantive issues pertinent to student motivation and engagement. The empirical evidence presented here is drawn from various

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 187–216.

research studies underpinned by the Motivation and Engagement Wheel – a comprehensive and integrative framework to study a diverse range of key motivation and engagement factors – and its accompanying assessment tool, the Motivation and Engagement Scale or MES (Martin, 2007, 2009). In the first section, we briefly review CFA and SEM, their unique advantages over statistical techniques under the umbrella of general linear modeling (GLM), and also their key role in a construct validation approach to research. In the second section, we then introduce the Wheel, summarise its theoretical bases, and describe the MES. In the third section, we review research studies that employ CFA in assessing the relative multidimensionality and specificity of motivation and engagement factors across various academic domains, over diverse samples, and between distinct units or levels of analysis. In the fourth section, we present examples of large-scale longitudinal SEM studies that seek to test theoretically hypothesized models linking academic motivation and engagement to their antecedents and outcomes. In this section, we also report on the use of ESEM on responses to the MES. Finally, in the fifth section, we point out some key areas of recent development in latent variable techniques (i.e., composite-score latent modeling, cross-lagged latent modeling, latent variable interaction, and latent growth modeling) that offer future methodological opportunities for educational psychology researchers seeking to establish more reliable empirical evidence that supports educational policy and practice.

THE ROLE OF CFA AND SEM IN CONSTRUCT VALIDATION

Construct Validation Approach to Research

Given the latent and unobserved nature of the majority of psycho-educational constructs (e.g., academic motivation), researchers have proposed a *construct validation* approach to educational psychology research (Marsh & Hau, 2007; Marsh, Martin, & Hau, 2006; Martin, 2007; Martin, Green, Colmar, Liem, & Marsh, 2011). This approach essentially focuses on the interplay between the theoretical conceptualisation of the target construct under examination and its measurement validation. Thus, the main issue at the heart of this approach concerns the extent to which a latent construct is well represented or well defined by its manifest indicators and the extent to which the latent factor is positively related to other latent constructs that are theoretically and conceptually compatible or congruent (e.g., mathematics self-efficacy and mathematics self-concept); negatively related to other latent constructs that are theoretically and conceptually opposing or antithetical (e.g., mathematics self-efficacy and mathematics test anxiety); and trivially or non-significantly related to other latent constructs that are not theoretically and conceptually associated (e.g., mathematics self-efficacy and physical self-concept). Accordingly, studies that adopt a construct validation approach can be classified as *within-network* or *between-network* studies with the former concerned with the internal structure of an instrument comprising sets of items serving as indicators of distinct latent constructs that the instrument purports to measure, and the latter seeking to establish a logical and theoretically consistent pattern of relationships between a given latent construct and its conceptually related latent constructs (in the case of convergent validity) or conceptually dissimilar latent constructs (in the case of discriminant validity).

CFA and SEM

In the context of the construct validation approach, CFA and SEM are two major groups of latent variable modeling techniques that predominantly underpin within-network and between-network analytic frameworks, respectively. It is important to note that these modeling techniques, when appropriately employed, have various advantages over traditional, non-latent variable analytic tools such as exploratory factor analysis or regression analysis. First, these statistical procedures allow researchers to investigate correlational data by specifying *a priori* the expected factor structure for the measures under investigation as well as the associations and/or predictive paths between latent constructs, thereby encouraging the researcher to base predictions on extant theorising and prior research rather than relying on exploratory approaches. Second, unlike many other techniques, latent variable modeling can be effectively used to test the entire hypothesized model and its complex predictive relationships amongst factors in one analysis, a procedure that is particularly important for testing theoretical models in educational psychology. Third, latent variable modeling also takes into account the presence of measurement errors associated with observed indicators, thereby providing more accurate estimated parameters for inter-factor relationships. Fourth, latent variable modeling allows us to assess the invariance of key measurement parameters in CFA (i.e., factor loadings, factor correlations, error terms) and predictive paths in SEM (i.e., regression weights) across groups involved in the investigation (e.g., female and male students, early and later adolescents) to determine whether these groups come from the same population and, therefore, justify pooling responses across groups and draw a broad conclusion of findings (or otherwise, in cases where invariance is not established).

Whilst a technical discussion of CFA and SEM is beyond the scope of this chapter, it is considered sufficient to provide a brief description of each of these techniques (for more detailed accounts of CFA and SEM, see e.g., Byrne, 2012; Kline, 2011). In CFA, it is hypothesized that (a) each measured indicator will have a non-zero loading onto the factor it is designed to measure and a zero loading onto all other factors, (b) all latent factors are correlated (i.e., when a measurement model comprises more than one latent factor), and (c) the error terms (often referred to as item uniquenesses) for each measured variable are uncorrelated (unless specified otherwise, see below). Furthermore, within a CFA framework, a higher-order latent factor can be generated by setting specific lower-order latent factors as "defining indicators" of the hypothesized higher-order latent factor. Figure 1 shows a pictorial representation of *measurement* and *structural* components of a two-latent factor model. The CFA component is represented in this figure by two measurement models embodying two latent factors (LF1 and

LF2), each of which is defined by three indicators (Item 1, Item 2, and Item 3 for LF1 and Item 4, Item 5, and Item 6 for LF2) while taking into account their associated error terms (e1, e2 e3, e4, e5, and e6). Figure 1 also shows a predictive relationship between LF1 and LF2, representing the structural component of the model. It is important to note that whilst there are only two latent factors in this example, which is built for illustrative purposes, latent variable models hypothesized and tested in educational psychology research are typically more comprehensive and reflective of the complexity of the relationships of numerous latent factors (see our examples below). In summary, in latent variable modeling, psycho-educational constructs are represented by latent factors corrected for measurement errors or unreliability and the complexity of structural relationships of such constructs can be simultaneously estimated in a one-step analysis of the proposed model. Further, the fit between the data and the model can be assessed through evaluating various fit indices. In the following section, we describe a conceptual framework that underpins a motivation and engagement research program that has chiefly capitalized on the flexibility and versatility of CFA and SEM.

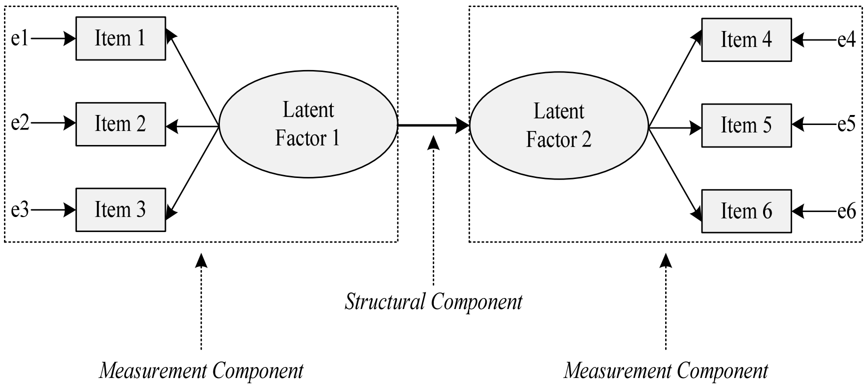

Figure 1. Measurement and structural components of a two-latent factor structural equation model (adapted with permission from Martin, Green, Colmar, Liem, & Marsh, 2011). Note: e = error term of manifest indicator (i.e., item uniqueness)

MOTIVATION AND ENGAGEMENT: A CONCEPTUAL MODEL AND ITS ASSESSING INSTRUMENT

Across various areas of human endeavour, motivation and engagement play a key role in adaptive developmental pathways and the pursuit of desirable outcomes. In the educational setting, students' motivation and engagement are key to their achievement, interest in school, and enjoyment of study, among others (Schunk, Pintrich, & Meece, 2008). However, there has been some concern amongst theorists and practitioners that research and theories in the field lack practical/applied utility (Urdan & Turner, 2005) and that a good deal of research in this area is guided by diffuse theoretical perspectives (Murphy & Alexander, 2000). It is thus not surprising there have been calls to give greater attention to "use-inspired basic research" (Pintrich, 2003, p. 668) and for more integrative approaches to theorising and research in this field (e.g., Murphy & Alexander, 2000; Wigfield & Cambria, 2010). In response to these calls, the Motivation and Engagement Wheel (Figure 2) and its accompanying assessment tool, the Motivation and Engagement Scale (MES), were developed to enable more encompassing and integrative study of motivation and engagement (Martin, 2007, 2009; see also Liem & Martin, 2012).

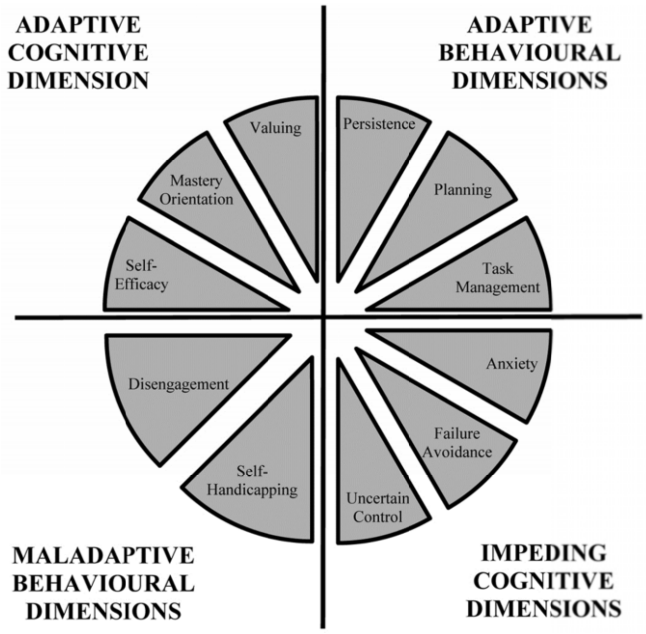

Figure 2. Motivation and Engagement Wheel (reproduced with permission from Martin, A. J. (2010). Building classroom success: Eliminating academic fear and failure. London: Continuum)

The Motivation and Engagement Wheel

Within this conceptual framework, motivation is defined as individuals' inclination, energy and drive to learn, work effectively, and achieve to their potential, whereas engagement as the behaviours aligned with this energy and drive (Martin, 2007, 2009) (however, we recognise that other feasible and cognate conceptual definitions exist). Based on this definition, the Wheel was developed as a multidimensional framework representing salient cognition and behaviour pertinent to motivation and engagement. Specifically, it was built upon two basic congruencies across various models. The first reflects the distinction between cognitive and behavioural dimensions of achievement pursuit, including theorizing and research focusing on cognitive and behavioural dimensions to academic engagement (Fredricks, Blumenfeld, & Paris, 2004), cognitive and behavioural orientations of learning strategies (Pintrich & Garcia, 1991; Zimmerman, 2008), cognitive antecedents of behavioural strategies used to negotiate environmental tasks (Buss & Cantor, 1989), and also cognitive-behavioural approaches to engagement and behaviour change (Beck, 1995). The second relates to hierarchies within the self-system that reflect the representation of specific factors under more global dimensions (e.g., self-concept, see Marsh & Shavelson, 1985; personality traits, see Digman, 1997). Taken together, these considerations led to conceptualising the Wheel in terms of higher- and first-order cognitive and behavioural dimensions.

At its most basic level, as Figure 2 shows, the Wheel comprises four higher-order dimensions, including adaptive cognition, representing an adaptive motivational orientation to learning/task; adaptive behaviour, reflecting beneficial strategies that individuals adopt to engage in their learning/task; impeding cognition, representing an orientation that inhibits motivated engagement in learning/task; and maladaptive behaviour, reflecting detrimental strategies that individuals engage in approaching their learning/task. At the more specific level, the 11 first-order dimensions of factors were chosen to integrate seminal theories such as self-efficacy, attribution and control, valuing, achievement goal orientation, need achievement, self-worth, self-determination, and self-regulation (Martin, 2007, 2009). In terms of adaptive cognition , the self-efficacy dimension is guided by self-efficacy and self-agency perspectives (Bandura, 1997); the valuing dimension is informed by expectancy-value theory (Wigfield & Eccles, 2000); and the mastery orientation dimension represents the concept of mastery in achievement goal perspectives (Kaplan & Maehr, 2007) and the notion of intrinsic motivation in self-determination theory (Ryan & Deci, 2000). The three adaptive behaviour dimensions – planning, task management, and persistence – represent central learning strategies in the self-regulatory perspective (Pintrich & Garcia, 1991; Zimmerman, 2008). For impeding cognition, the uncertain control dimension constitutes the controllability element of attribution theory (Connell, 1985; Weiner, 1994); and the failure avoidance and anxiety dimensions represent impeding cognitive factors in achievement need/motive and self-worth perspectives (Atkinson, 1957; Covington, 1992). Lastly, in terms of maladaptive behaviour, the self-handicapping dimension represents behavioural strategies aimed at avoiding failures and protecting one's self-worth (Covington, 1992); and the disengagement dimension constitutes a negative behavioural consequence of self-appraisals about ability and/or tasks in the achievement context (Skinner, Kindermann, Connell, & Wellborn, 2009). Taken together, these factors seek to represent an encompassing set of motivation and engagement factors derived from contemporary psycho-educational theorizing and research.

Table 1. Definitions and sample items from the Motivation and Engagement Scale – High School (MES-HS)

No.	Scale/Subscale	Operational Definition	Sample Item
Adaptive Cognition		*Attitudes and orientations facilitating learning*	
1.	Self-efficacy	Students' belief and confidence in their own ability to do well in their learning.	"If I try hard, I believe I can do my schoolwork well"
2.	Valuing	Students' belief about the usefulness, importance, and relevance of the academic work they engage in.	"Learning at school is important to me"
3.	Mastery orientation	Students' orientation to developing competence and knowledge in their learning.	"I feel very pleased with myself when I really understand what I am taught at school"
Adaptive Behaviour		*Behaviours and engagement facilitating learning*	
4.	Planning	The extent to which students plan their academic work and tasks.	"Before I start an assignment I plan out how I am going to do it"
5.	Task management	The ways students use their time, organise their timetable, and choose and arrange where they work.	"When I study, I usually study in places where I can concentrate"
6.	Persistence	The extent to which students sustain their engagement.	"If I can't understand my schoolwork at first, I keep going over t until I understand it"
Impeding Cognition		*Attitudes and orientations impeding learning*	
7.	Anxiety	The extent to which students feel anxious when they think about or do their academic work.	"When exams and assignments are coming up, I worry a lot"
8.	Failure avoidance	The extent to which students' motivation to do their work is to avoid failure, doing poorly, or disappointing others.	"Often the main reason I work at school is because I don't want to disappoint my parents"
9.	Uncertain control	The extent to which students are uncertain about how to do well or how to avoid doing poorly.	"I'm often unsure how I can avoid doing poorly at school"
Maladaptive Behaviour		*Behaviours and engagement maladaptive for learning*	
10.	Self-handicapping	The extent to which students compromise their chances of academic success so they have excuses if they do not do well.	"I sometimes don't study very hard before exams so I have an excuse if I don't do as well as I hoped"
11.	Disengagement	Students' inclination to give up in their academic work or in achievement setting more generally.	"I often feel like giving up at school"

Note: adapted with permission from Liem and Martin (2012)

The Motivation and Engagement Scale

Alongside the Wheel is the Motivation and Engagement Scale or MES (Martin, 2007, 2009; see also Liem & Martin, 2012 for a systematic review of the instrument). The MES consists of 11 motivation and engagement subscales congruent with the 11 first-order factors in the Wheel (viz. self-efficacy, valuing, mastery orientation, planning, task management, persistence, anxiety, failure avoidance, uncertain control, self-handicapping, and disengagement). The 11 subscales can be grouped into four major scales representing the four higher-order motivation and engagement dimensions (i.e., adaptive cognition, adaptive behaviour, impeding cognition, and maladaptive behaviour). Each of the 11 MES subscales comprises four items – hence the MES is a 44-item instrument. To respond to the MES, a 7-point Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree), is provided – with a 1 (strongly disagree) to 5 (strongly agree) scale for use with elementary/primary school students (see Martin, 2009). Definitions of the MES subscales and sample items of the MES-HS (i.e., High School version of the MES) are presented in Table 1. The MES comprises a suite of corresponding instruments that aim to assess motivation and engagement in diverse applied settings including elementary school, high school, university/ college, sport, music, and work. Its applications across these domains are on the basis that core motivation and engagement factors relevant to human performance in these various settings are congruent (Martin, 2007, 2009).

CFA AND SEM IN PRACTICE: THEIR ROLE IN ADDRESSING APPLIED AND SUBSTANTIVE ISSUES IN MOTIVATION AND ENGAGEMENT

As elucidated above, to illustrate the use of CFA and SEM in educational psychology, we draw on a program of research underpinned by the Motivation and Engagement Wheel and, more specifically, based on various analyses of responses to the MES. Aligned with the construct validation approach to research, the illustrative cases reviewed in the present chapter are divided into two sections. We first report on studies pertinent to the *within-network* framework of construct validation, that is, those that employed various applications of CFA. We then report on studies relevant to the *between-network* framework of construct validation, that is, those that harnessed distinct applications of SEM.[i]

CFA in Practice

First- and higher-order confirmatory factor analysis. One of the more basic applications of CFA is to assess the factor structure of a multidimensional instrument. Researchers can assess first-order factor structures or higher-order factor structures. An example of a first-order factor is where factors are developed from items in a survey. Thus, in the case of the MES, four self-efficacy items 'load' onto a factor that is declared a self-efficacy (latent) factor. The same operation is formed for each of the four items for each of the other ten scales in the MES to form a total of 11 latent factors (see Figure 4a).

Researchers may also examine higher-order structures where the first-order factors are collected together as indicators to form a 'higher' factor. Thus, a higher-order factor structure would comprise survey items that load onto a number of first-order factors and these first-order factors in turn load onto a higher-order factor. In the case of the MES, for example, 12 items form three first-order factors – self-efficacy, valuing school, and mastery orientation – and these three factors in turn load onto a higher-order factor referred to as 'adaptive cognition' (see Figure 4b).

For example, using LISREL 8.54 (Jöreskog & Sörbom, 2003), Martin (2007) performed first-order and higher-order CFAs of 12,237 students' responses to the MES-HS. The results showed an excellent fit of the data to the first-order model (see Figure 4a; χ^2 = 15,737.26, *df* = 847, NNFI = .98, CFI = .98, RMSEA = .038) as well as to the higher-order model (see Figure 4b; χ^2 = 20,280.91, *df* = 886, NNFI = .97, CFI = .98, RMSEA = .042). In these analyses, all first- and higher-order factor loadings were significant and substantial (means of factor loadings $\geq$ .66). Inter-factor correlations were consistent with the directions predicted by the theories underlying the constructs. That is, all the adaptive factors were significantly positively correlated with one another and these factors were markedly negatively correlated with the maladaptive factors and non-significantly correlated with the impeding factors. Moreover, as reflected in a change of CFI<.01 (Cheung & Rensvold, 2002), a series of multigroup CFAs of the first-order model confirmed the invariance of key measurement parameters (factor loadings, factor correlations, and item uniquenesses) over gender and also across junior, middle, and senior high schools. Taken together, these first- and higher-order CFAs showed that the MES-HS is a psychometrically sound instrument and that the Wheel is a conceptually and theoretically sound framework to measure and understand an integrative set of first- and higher-order motivation and engagement dimensions important to student academic development.

Specificity of motivation and engagement across academic subjects. Another example of CFA application is derived from a study that sought to evaluate the relative domain specificity of student motivation and engagement in different academic subjects (Green, Martin, & Marsh, 2007). The study was initiated by the observation that the majority of extant research has either examined student motivation and engagement in a general academic domain or focused on only a single academic subject. In this context, the study aimed to examine the extent to which student motivation and engagement are multidimensional – as posited in the Wheel – and further distinguished across English, mathematics, and science. To address this, Green and colleagues administered the MES-HS to 1,801 high school students (33% female; mean age = 14.40 years, SD = 1.40) who rated their motivation and engagement in mathematics and another academic area (English or science). Green and her colleagues focused on testing three CFA models hypothesized to reflect construct and domain specificity, domain generality, and construct generality, respectively, of the motivation and engagement dimensions in the Wheel (see Figure 3). The first model, a domain and construct specific model (Figure 3a), is a 33-factor model in which the 11 motivation and engagement first-order facets in each of the three subjects were estimated (e.g., English self-efficacy, mathematics self-efficacy, science self-efficacy, etc.). The second model, a domain general model (Figure 3b), is an 11-factor model, whereby English, mathematics, and science items jointly load onto each of the 11 motivation-and-engagement factors (e.g., domain-general self-efficacy, domain-general valuing, etc.). The third model, a construct general domain (Figure 3c), is a 3-factor model, in which all of the subject-specific items define a subject-specific motivation-and-engagement general construct. In each of these models, CFA on responses to 132 subject-specific items of the MES-HS was performed using LISREL 8.72 (Jöreskog & Sörbom, 2005). Methodologically, it is important to recognize that in CFA parallel indicators (e.g., English, mathematics, and science parallel items) potentially pose statistical issues in that their measurement errors may strongly co-vary and, the absence of these covariances in specifying a CFA model would lead to biased parameter estimates (e.g., inflated associations between latent factors; see Marsh & Hau, 1996; Marsh, Roche, Pajares, & Miller, 1997). For this reason, uniquenesses of parallel items across academic domains were also freely estimated in the analysis.

The results showed that whilst each model generated acceptable fit to the data, the 33-factor model yielded the best fit (χ^2 = 16,497.26, df = 7,854. RMSEA = .025) which was significantly better than the 11-factor (χ^2 = 24,422.63, df = 8,327, RMSEA = .033) and 3-factor (χ^2 = 8,524.26, df = 8,379, RMSEA = .045) models. This finding demonstrated that student motivation and engagement were multidimensional and specific to each academic area. Further, the majority of between-subject correlations of corresponding motivation or engagement factors (e.g., English and mathematics self-efficacy, English and science self-efficacy) hovered around r = .60s, suggesting that although each motivation or engagement construct shared considerable variance across academic subjects (around 36%), the correlations were not so high that they essentially represented the same construct. Equally important were the findings pertaining to the different correlational patterns across distinct motivation and engagement dimensions. Specifically, valuing of subject was found to have relatively lower correlations (r_{range} = .52 and .62), suggesting that students' valuing of a particular school subject was not so highly reflective of their valuing of other subjects. Conversely, anxiety – with relatively high shared variance across subjects (r_{range} = .79 and .86) – appeared to be more generalized across domains. Collectively, whilst motivation and engagement in English, mathematics, and science were essentially multidimensional and domain specific, this domain specificity was relatively nuanced in that some dimensions (e.g., valuing) were more domain specific whereas some others (e.g., anxiety) were more domain general. The findings hold important educational implications in that students' endorsement of the former (e.g., valuing) may better be fostered at a subject specific level, whereas that of the latter (e.g., anxiety) can be effectively addressed by implementing a more general approach across different academic areas.

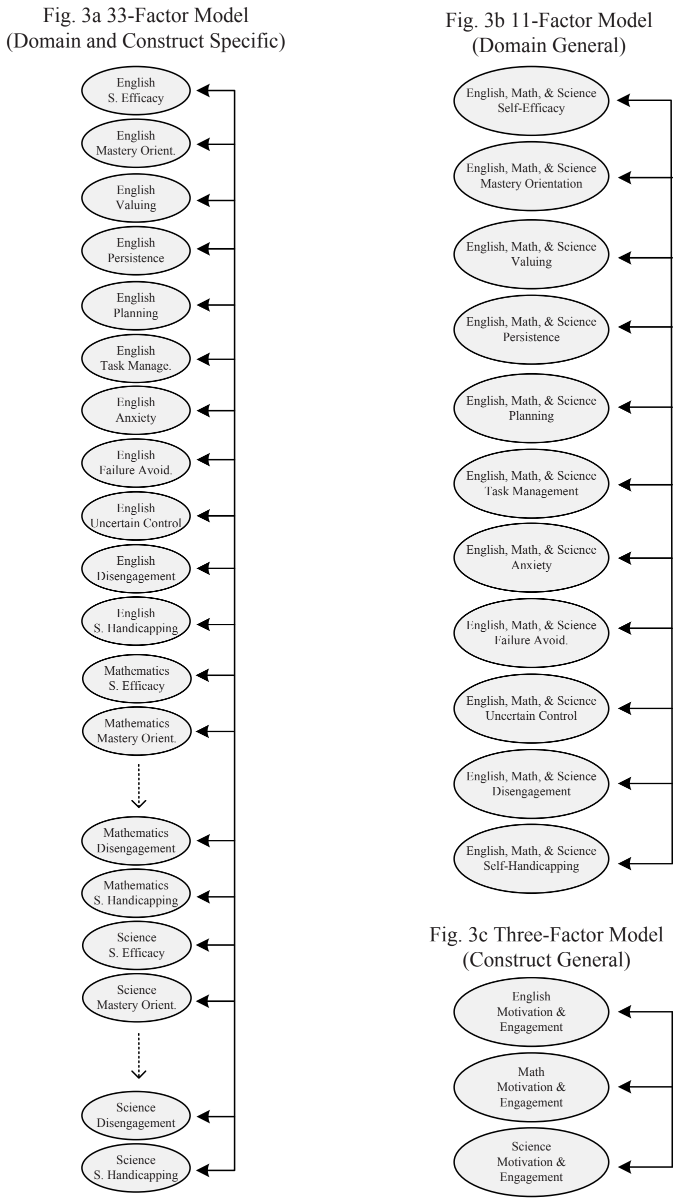

Figure 3. Hypothesized confirmatory factor analysis (CFA) models reflecting domain and construct specificity, domain generality, and construct generality of English, mathematics, and science motivation and engagement (adapted with permission from Green, Martin, & Marsh, 2007). Note: For clarity purposes, manifest indicators (items) and their corresponding error terms are not shown.

A developmental construct validity approach to motivation and engagement. The second example of CFA application focuses on the assessment of the construct validity of student motivation and engagement across elementary, high school, and university/college samples. The rationale underpinning this research is that students of different educational levels share a great deal of commonalities in their efforts to sustain their academic motivation and engage in their academic learning over the course of their education. To this end, Martin (2009) administered the MES-Junior School (MES-JS) to 624 upper-age elementary students (56% female, mean age = 11.13, SD = 0.69) and the MES-University/College (MES-UC) to 420 undergraduate students (80% female, mean age = 21.47, SD = 6.62). For the high school sample, an archived database comprising responses to the MES-HS of 21,579 high school students (around 45% female; mean age = 14.52, SD = 1.57) was used. Consistent with the more widely used MES-HS, the MES-JS and MES-UC each comprises 44 items and measures the same number of first-order (11) and higher-order (4) factors (see Liem & Martin, 2012). Item adaptation was done to make simple and transparent word and terminology changes in order to remain very parallel to the high school form. Conducting CFA using LISREL 8.80 (Jöreskog & Sörbom, 2006), Martin examined both first-order and higher-order factor structures of the MES separately for each sample (Figure 4). For the 11-first-order-factor model (Figure 4a), the CFA yielded a very good fit to the data for elementary school (χ^2 = 1,881.10, *df* = 847, CFI =.98, NNFI = .97, RMSEA = .04), high school (χ^2 = 28,217.75, *df* = 847, CFI =.98, NNFI = .98, RMSEA = .04), and university (χ^2 = 1,697.75, *df* = 847, CFI =.96, NNFI = .95, RMSEA = .05) samples and all the items were significant indicators of their respective a priori latent factors with the majority of item factor loadings above .60. In addition, the higher-order factor structure (Figure 4b), in which correlations between first-order factors were constrained to be zero and their relationships were explained in terms of higher-order factors, also yielded a very good fit for elementary school (χ^2 = 2,155.87, *df* = 886, CFI =.97, NNFI = .97, RMSEA = .05), high school (χ^2 = 36,732.07, *df* = 886, CFI =.98, NNFI = .98, RMSEA = .04), and university (χ^2 = 1,968.82, *df* = 886, CFI =.95, NNFI = .94, RMSEA = .05) samples.

To assess the invariance of key measurement parameters, Martin (2009) conducted a series of multigroup CFAs assessing the MES factor structures across the distinct groups within each sample (male and female students; younger and older students) and between samples (elementary, high school, and university students). Multigroup CFA essentially involves comparison of a number of models in which measurement parameters (i.e., first-order and higher-order factor loadings, first-order or higher-order factor correlations, uniquenesses) are systematically held invariant across groups and assessment of changes in fit indices relative to a baseline model that allows all the measurement parameters to differ across groups.

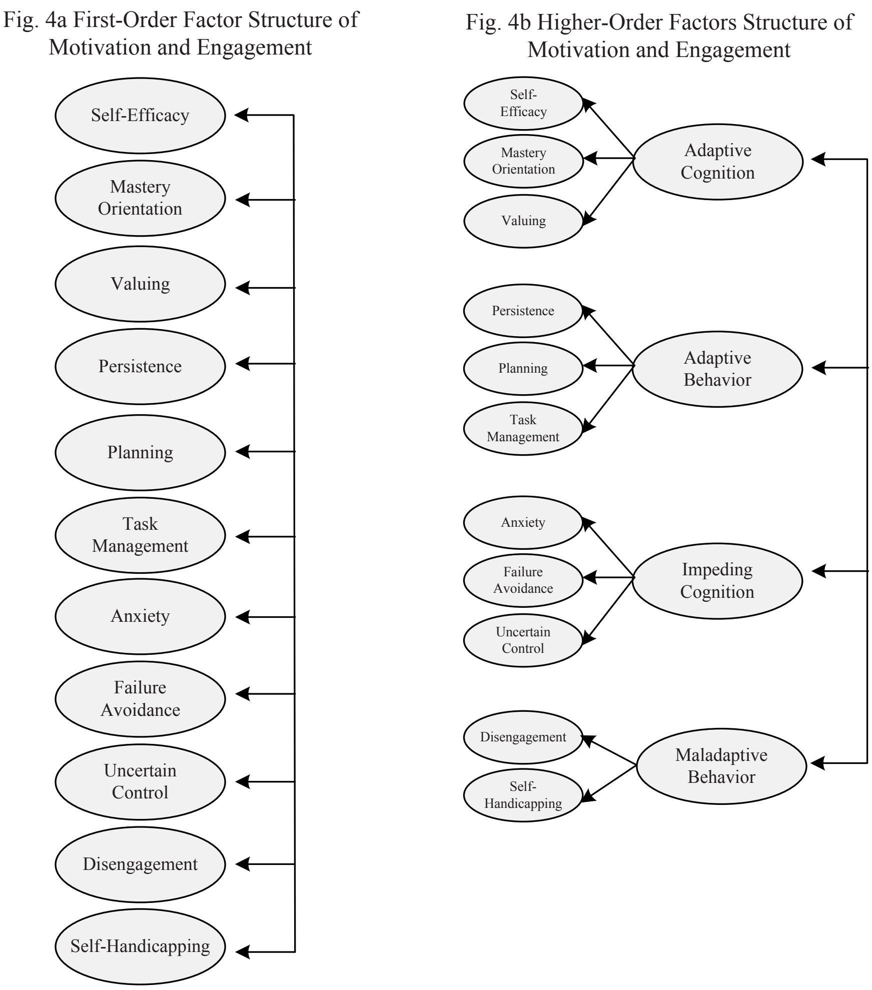

Figure 4. First-order and higher-order hypothesized CFA models of motivation and engagement (adapted with permission from Martin, 2009). Note: For clarity purposes, manifest indicators (items) and their corresponding error terms are not shown.

Based on the application of recommended criteria for evidence of lack of invariance (i.e., a change of <.01 in CFI, see Cheung & Rensvold, 2002; a change of <.015 in RMSEA, see Chen, 2007), findings indicated the presence of the invariance of measurement parameters across groups within each sample and across samples. It is also important to note that evidence for between-group invariance in measurement parameters (factor correlations, uniquenesses, and especially factor loadings) is a basic prerequisite in conducting valid comparison of means between groups (Marsh, 1993) in that observed mean differences, if any, can be regarded 'trustworthy' as measurement properties between groups are equivalent.

To assess mean difference within the context of CFA, Kaplan (2000) suggested a multiple-indicators multiple-causes (MIMIC) approach, which is similar to a regression model in which, in the present study, latent factors of motivation and engagement were "caused" by discrete grouping variables (e.g., gender) each represented by a single indicator. Given the presence of multinominal predictors, high school students were used as the reference group and two dummy variables were created: high school (0) versus elementary school (1) and high school (0) versus university (1); hence, positive beta weights for dummy variables would indicate higher scores for elementary school and university students relative to high school students, and *vice versa*. MIMIC modeling of the first-order model showed a good fit to the data (χ^2 = 39,347.85, df = 914, CFI =.95, NNFI = .94, RMSEA = .04), as did the higher-order model (χ^2 =45,508.66, df = 966, CFI =.95, NNFI = .94, RMSEA = .05). Specifically, findings showed that, relative to high school students, elementary and university students were significantly higher on adaptive cognition (β = .45 and β = .36, respectively) and adaptive behaviour (β = .35 and β = .36, respectively) but were significantly lower on impeding cognition (β = -.47 and β = -.24, respectively) and maladaptive behaviour (β = -.49 and β = -.24, respectively). A general similar pattern was also observed with the first-order motivation and engagement factors. Taken all together, Martin (2009) provided evidence that academic motivation and engagement of elementary, high school, and university students can be analogously represented by both first-order and higher-order models in the Wheel. It was further concluded that measurement of these motivation and engagement factors can be conducted equivalently across the three educational levels. This evidence, in turn, warrants the comparison of the degree of motivation and engagement factors amongst students from different developmental stages or educational levels.

Multilevel confirmatory factor analysis. An emerging line of research, representing a contextualist perspective, focuses on understanding the role of context, and how this context interplays with student motivation and engagement, in predicting key educational outcomes (see e.g., Lüdtke, Robitzsch, Trautwein, & Kunter, 2009; Marsh, Lüdtke, Robitzsch, Trautwein, Asparouhov, Muthen, & Nagengast, 2009; Miller & Murdock, 2007). It is now widely recognized, however, that the same construct (e.g., self-efficacy) and its associations with other constructs, but measured at different units or levels of analysis (e.g., student level vs. school level), may lead to fundamentally different interpretations. Furthermore, a student-level factor structure might not be replicated at the upper (e.g., class, school) levels (Klein & Kozlowski, 2000; Marsh, Martin, & Cheng, 2008; Van de gaer, Grisay, Schulz, & Gebhardt, 2012). That is, measures with good psychometric properties at the individual level may not be satisfactory at the class or school level. It is therefore important to establish the psychometric evidence of context-level measures at the upper levels before assessing their role as contextual predictors of student-level outcomes.

Given this, Martin, Malmberg, and Liem (2010) conducted a series of multilevel CFAs using *Mplus* (Muthén & Muthén, 1998-2010) and provided evidence for various multilevel factor structures of the MES-HS based on responses of over 21,000 students in 58 schools. As shown in Figure 5, Martin and colleagues tested various multilevel CFA models including a one-factor model in which a first-order motivation/engagement factor (e.g., self-efficacy) was represented by a latent factor defined by its four *a priori* items (Figure 5a); a three-factor model in which three first-order motivation/engagement factors (e.g., self-efficacy, mastery orientation, valuing) that belong to the same higher-order dimension (or two-factor model for maladaptive behaviour) were each represented by a latent factor defined by two parcels of two randomly selected items (Figure 5b); one-factor higher-order model in which three first-order (or two first-order factors for maladaptive behaviour) motivation/engagement factors that belong to the same higher-order dimension (e.g., self-efficacy, mastery orientation, valuing) constitute the first-order latent factors defining their *a priori* higher-order latent factor (i.e., adaptive cognition; Figure 5c); and a four-factor cluster model in which the four higher-order motivation/engagement dimensions were simultaneously estimated and that each dimension was defined by the scale scores of their *a priori* first-order motivation/engagement factors (Figure 5d). Their findings demonstrated that, at student and school levels, the various CFA models tested evinced sound factor structure and good model fit. Further, the results showed that factor correlations were in the hypothesized directions and broadly parallel at the student and school levels. Taking these findings together, the study suggests that the different ways of conceptualizing the multidimensionality of motivation and engagement are viable at both student and school levels and that the MES-HS target factors and the framework from which they emanate (the Motivation and Engagement Wheel) demonstrates sound multilevel psychometric properties. This evidence is a basis for future research to use school-level MES motivation and engagement factors as contextual predictors of student-level motivation and engagement as well as other educational outcome factors (e.g., academic performance).

SEM in Practice

Longitudinal mediated model of academic buoyancy. The first example of SEM application draws from a study on academic buoyancy (Martin & Marsh, 2006, 2008) conceptualized as students' capacity to successfully deal with setbacks and challenges that are typical of everyday academic life (e.g., receiving poor grades, negative feedback). Prior research has indicated the predictive role of academic buoyancy in enjoyment of school, class participation, general self-esteem (Martin & Marsh, 2006) and also in absenteeism (negatively), task completion, and educational aspiration (Martin & Marsh, 2008). This prior work has also identified the '5Cs' of academic buoyancy, including confidence (high self-efficacy), coordination (high planning), commitment (high persistence), composure (low

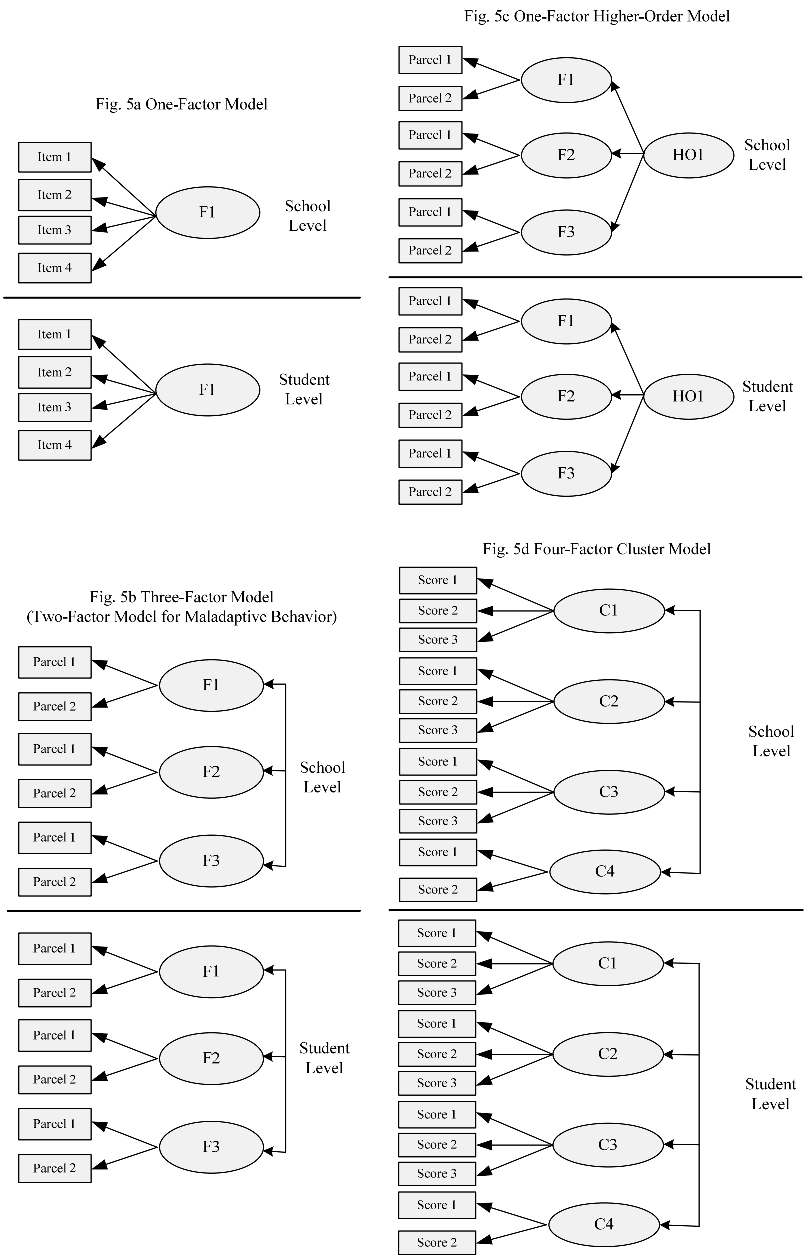

Figure 5. Various multilevel confirmatory factor analysis (CFA) models of motivation and engagement (adapted with permission from Martin, Malmberg, & Liem, 2010). Note: For clarity purposes, error terms of manifest indicators are not shown

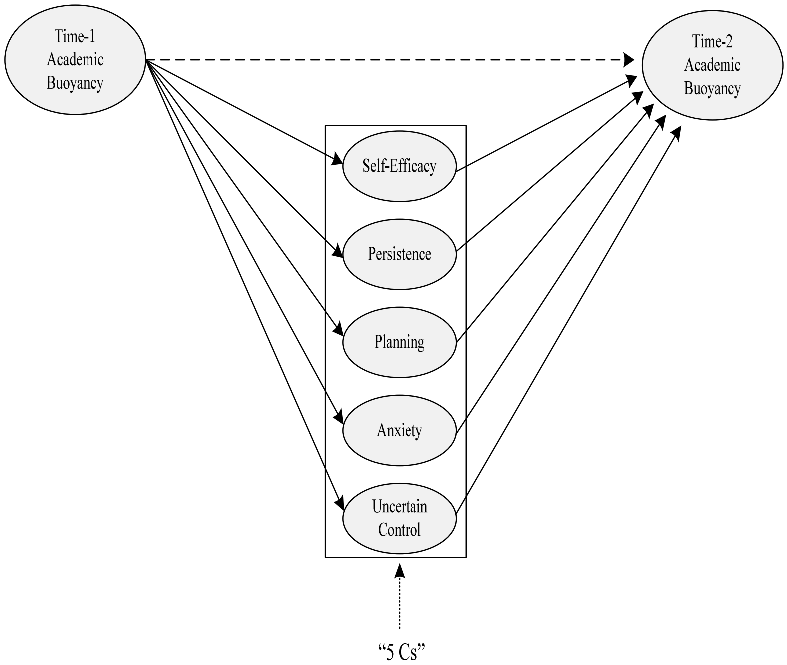

Figure 6. Hypothesized fully-forward structural equation model predicting Time2 academic buoyancy (adapted with permission from Martin, Colmar, Davey, & Marsh, 2010). Note: Dotted arrow represents auto-regressive path. For clarity purposes, manifest indicators (items) and their corresponding error terms are not shown

anxiety), and control (low uncertain control), as key motivational factors closely associated with academic buoyancy (Martin & Marsh, 2006). Building upon this research, Martin, Colmar, Davey, and Marsh (2010) examined the salience of the 5Cs in mediating prior and subsequent academic buoyancy (see Figure 6) by implementing a longitudinal research design in which academic buoyancy was assessed at two points in time (MacCallum & Austin, 2000; Martin, 2011; Menard, 1991; Rosel & Plewis, 2008). A key procedure for modeling longitudinal data is through autoregressive paths (MacCallum & Austin, 2000; Martin, 2011; Rosel & Plewis, 2008) which link variables measured at Time 1 with corresponding variables measured at Time 2. Hence, the effect of any remaining constructs on the Time 2 construct is viewed as beyond or 'over and above' that of the Time 1 construct. As seen in Figure 6, the key autoregressive path in this model was one that linked students' academic buoyancy with their academic buoyancy one year later. There were two major advantages for testing the hypothesized fully-forward model shown in Figure 6. First, the model allowed examining the effects of the

5Cs on Time 2 academic buoyancy after taking into account its variance shared with Time 1 buoyancy. Second, the ordering of factors in the model also enabled assessing the direct and indirect effects (mediated via the 5Cs) of prior academic buoyancy on subsequent academic buoyancy.

Martin and his colleagues (2010) tested the theoretically grounded model in Figure 6 with a sample of 1,866 high school students (39% female) from six Australian high schools completing the instrumentation at T1 (3rd term of the school year) and T2 (one year later). Approximately 29% of the respondents were in grade 7 (the beginning of high school) at T1 and grade 8 at T2; 24% were in grade 8 at T1 and grade 9 at T2; 23% were in grade 9 at T1 and grade 10 at T2; 18% were in grade 10 at T1 and grade 11 at T2, and 6% were in grade 11 at T1 and grade 12 (the final year of high school) at T2. The mean age of respondents was 13.86 years (SD = 1.28) at T1 and 14.79 years (SD = 1.28) at T2. Academic buoyancy was measured with the 4-item Academic Buoyancy Scale (ABS; Martin & Marsh, 2006, 2008; e.g., I think I am good at dealing with schoolwork pressures; I don't let a bad mark affect my confidence). Each of the 5Cs was measured by the self-efficacy, planning, persistence, anxiety, and uncertain control subscales of the MES-HS. Preliminary CFA conducted to assess the fit of the data to measurement models of the psycho-educational and socio-demographic factors in the hypothesized model (T1 and T2 buoyancy, the 5C components, gender, age) yielded an excellent fit to the data (χ^2 = 1,831.88, *df* = 367, CFI =.97, NNFI = .98, RMSEA = .05). A series of multigroup CFAs further showed that key measurement parameters (i.e., factor loadings, factor correlations, and item uniquenesses) were invariant across gender and age groups (as reflected by ΔCFIs<.01 between a baseline model that allowed all parameters to be different between groups and models that systematically constrained one, or more, set of parameters to be equivalent across groups; Cheung & Rensvold, 2002). This result justified pooling these sub-groups and analysing the whole sample as a single group. Having shown these preliminary results, the main SEM demonstrated that the hypothesized model fitted the data well (χ^2 = 1,831.87, *df* = 367, CFI =.97, NNFI = .98, RMSEA = .05). Of central relevance to the hypotheses, findings showed that after controlling for the effect of Time 1 academic buoyancy (β = .21, p<.001) and also those of gender and age, the 5Cs significantly predicted Time 2 academic buoyancy: self-efficacy (β = .22, p<.001), planning (β = .16, p<.001), persistence (β = .08, p<.05), anxiety (β = -.59, p<.001), and uncertain control (β = -.27, p<.001). Findings also showed that, alongside the direct effect of Time 1 academic buoyancy on Time 2 academic buoyancy, the effect of Time 1 academic buoyancy was partially mediated by the 5Cs – this was reflected in the decrease of its direct effect, which was initially β = .57 (p<.001), to be β = .21 (p<.001) after the inclusion of the 5Cs as mediators. Finally, the analysis also sought to assess if the central regression weights in the model (e.g., the predictive path between self-efficacy and Time 2 academic buoyancy) were equivalent across gender and age groups. Multigroup SEM indicated that the model that constrained regression paths (βs) to be equivalent across groups did not yield a significantly poorer fit (ΔCFI<.01) than the model that allowed these paths to differ across groups, suggesting that the predictive relationships between the central constructs in the model were not substantially different across gender and age groups. Collectively, these findings suggest that a psycho-educational intervention aimed at fostering students' academic buoyancy would do well when it addresses each of the 5C components and, further, such an intervention may well be effective when simultaneously implemented across the different socio-demographic sub-groups (boys and girls; younger and older adolescents).

Self-system model of engagement and disaffection. The second SEM example is derived from a recent large-scale longitudinal study (Green, Liem, Martin, Colmar, Marsh, & McInerney, 2012) that sought to test the self-system model of school engagement and disaffection (Skinner, Furrer, Marchand, & Kindermann, 2008; Skinner, Kindermann, Connell, & Wellborn, 2009; see Figure 7). The model posits dynamic relations between individuals' experience of context, self, engagement/disaffection, and outcomes. The notion of self is viewed as individuals' self-appraisals about their ability and task/activity (e.g., self-beliefs, subjective task values) developed through continuous socialization in an achievement context. Thus, the self in the model closely relates to the various motivational dimensions in the Wheel (Martin, 2007, 2009). The self-system model also posits that these self-appraisals lead to emotional or affective engagement (or disaffection) which in turn leads to behavioural engagement (or disaffection). It follows that these patterns of activity (or inactivity) potentially impact contextually-relevant outcomes including achievement and skill acquisitions. Skinner and her colleagues (2008, 2009) regard engagement (or disaffection) as the central component that reflects the manifestation of motivation and self-related beliefs on the one hand and affects outcomes on the other. As reflected in the model, they assert that engagement (a) directly predicts learning outcomes, (b) mediates the effects of 'self' on immediate outcomes, and (c) leads to subsequent changes in 'self', engagement, and outcomes. Effects of each component in the self-system model on its corresponding component over time (feed-forward effects) form a cycle that represents a continuous process of students' motivated engagement with their academic tasks/activities. This cycle explains why students who begin school academically engaged become more so, whereas students who start out academically disaffected become gradually more so as they progress through school (Skinner et al., 2009).

Of particular importance, the self-system model recognizes that each component of the model is multidimensional and, thus, this is the basis for Green and colleagues (2012) to establish and test a model comprising a comprehensive range of psycho-educational factors depicted in Figure 7. Specifically, the study conceptualized 'self' through academic motivation and self-concept; 'engagement' through its affective (positive attitudes toward school) and behavioural (class participation, homework completion, absenteeism) dimensions; and 'outcome' through test performance. In line with the self-system model (Skinner et al., 2008,

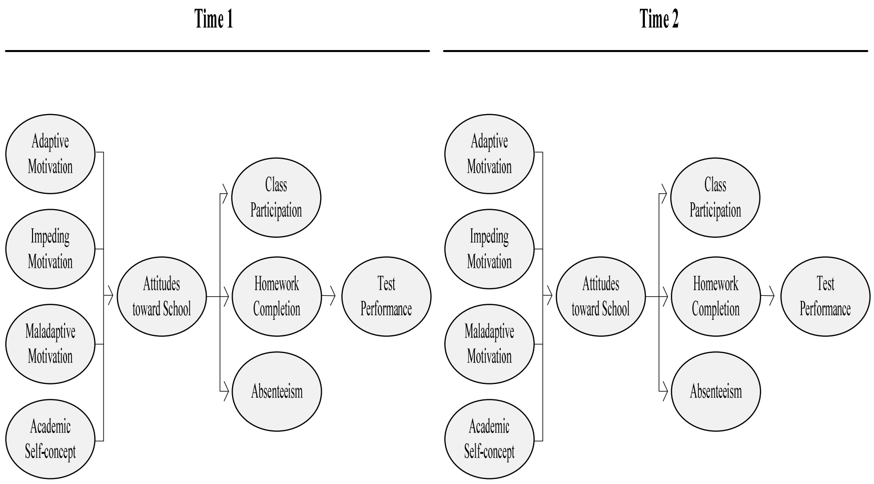

Figure 7. Hypothesized longitudinal structural equation model assessing the predictive relationships of academic motivation and self-concept, engagement, and achievement (adapted with permission from Green, Liem, Martin, Colmar, Marsh, & McInerney, 2012). Note: Motivation and attitudes toward school are higher-order factors. For clarity purposes, manifest indicators and their corresponding error terms are not shown

2009), comprehensive reviews of the literature provided support for the relationships of self, engagement, and outcome factors examined in the study. The hypothesized model was tested with the longitudinal sample in the academic buoyancy study described earlier (Martin et al., 2010). The motivational dimensions were measured by the MES-HS and academic self-concept by the Self-Description Questionnaire-Short (SDQ-S, Marsh, 1992; e.g., "I am good at most school subjects"). Two four-item scales, *positive school appraisals* ("I like school") and *positive academic intentions* ("I am happy to stay and complete school"), were used to measure students' positive attitudes toward school. *Homework completion* ("How often do you do and complete your homework and assignments?") was assessed on a 1 (never) to 5 (always) scale. *Class participation* was assessed by four items (e.g., "I get involved in things we do in class") and *absenteeism* ("How many days were you absent from school last term?") asked students to specify approximate days absent from school in the previous term. Responses to the absenteeism item were later coded on a scale of 1 (0 days absent) to 6 (5 or more weeks absent). The three psychometric scales of positive school appraisal, positive academic intentions, and class participation were adapted from Martin (2007, 2009) and were rated on a 1 (strongly disagree') to 7 (strongly agree) scale. Homework completion and absenteeism are single-item measures.

Preliminary analysis was focused on assessing the within-construct validity of the key psycho-educational factors in the model. This involved a CFA, performed with LISREL 8.80 (Jöreskog & Sörbom, 2006), of a longitudinal measurement model comprising 18 factors (9 factors for each time wave): four higher-order factors (adaptive, impeding, and maladaptive motivation and attitudes toward school) and five first-order factors (self-concept, class participation, homework completion, absenteeism, and test performance). This measurement model fitted the data well (χ^2 = 36,974.70, *df* = 7,922, CFI = .96, NNFI = .96, RMSEA = .06). All factor loadings were significant at p<.001 and substantial (>.69). Further, multi-group CFAs demonstrated gender and year-level (junior, middle, senior high school) measurement invariance of the longitudinal CFA (ΔCFIs< .01), providing justification for conducting whole-sample analyses. SEM performed with the model in Figure 7 yielded an excellent fit to the data (χ^2 = 23,991.29, *df* = 7,876, CFI=.98, NNFI=.98, RMSEA=.04). All the hypothesized paths were significant in the predicted directions (positive or negative). The results also indicated congruence of predictive paths across the two time waves, demonstrating the stability of the hypothesized model over time. That is, all Time 2 paths remained significant even after controlling for shared variance with the parallel Time 1 factors. For example, whilst adaptive motivation and academic self-concept were positive predictors of attitudes toward school both at Time 1 (β = .30 and β = .28, respectively, p<.001), maladaptive motivation negatively predicted this affective engagement at both Time 1 (β = -.47, p<.001) and Time 2 (β = -.41, p<.001). Attitudes toward school positively predicted class participation and homework completion at both Time 1 (β = .60 and β = .53, respectively, p<.001) and Time 2 (β = .48 and β = .29, respectively, p<.001), and negatively predicted absenteeism at both Time 1 (β = -.18, p<.001) and Time 2 (β = -.21, p<.001). Findings also showed that whilst class participation and homework completion positively predicted test performance at both Time 1 (β = .07, p<.05 and β = .24, p<.001, respectively) and Time 2 (β = .05, p<.05 and β = .07, p<.001, respectively), absenteeism negatively predicted test performance at both Time 1 (β = -.14, p<.001) and Time 2 (β = -.09, p<.001). Furthermore, Time 1 factors positively predicted their parallel Time 2 factors (test-retest or autoregressive paths), supporting the posited long-term effects of the key factors in the model that lead to either a *virtuous* or *vicious* cycle (Skinner et al., 2009). As asserted by Martin (2011), longitudinal SEM analyses may effectively provide a basis for proposing prescriptive statements on educational practices, especially given the temporal ordering of factors in the longitudinal models tested. This being the case, the longitudinal self-system model demonstrated here holds important implications in that an educational intervention that seeks to promote students' academic motivation and self-concept is potentially effective in promoting students' engagement and achievement and these effects are likely to be sustained over time.

Exploratory structural equation modeling. It is now recognized that measures of multidimensional constructs often fall short in meeting the standards of good measurement when responses to their items are subjected to CFA. This is reflected, for example, in poor fit indices, lack of between-group measurement invariance,

Fig. 8a Three-Factor CFA Model

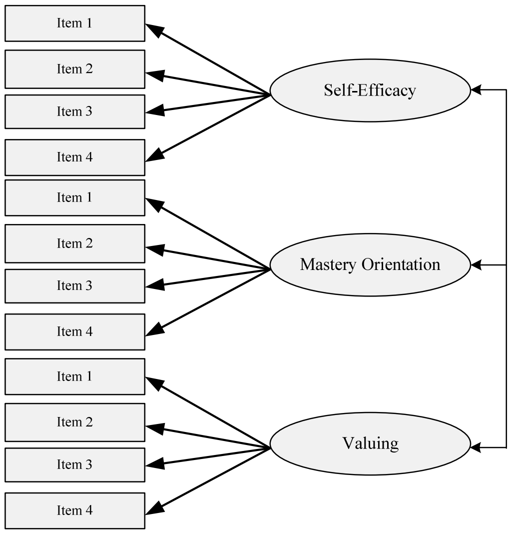

Fig. 8b Three-Factor ESEM Model

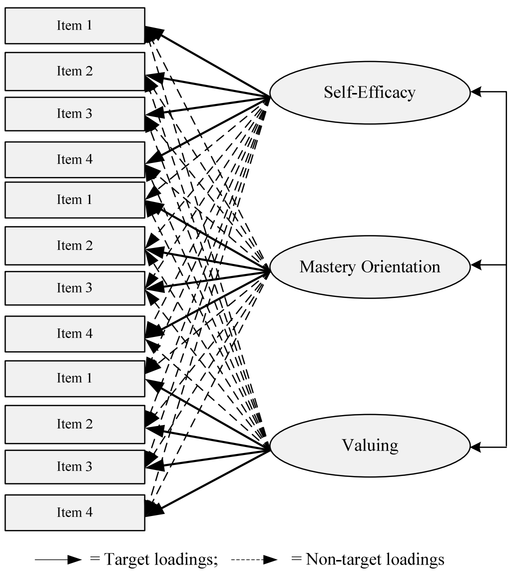

Figure 8. Confirmatory factor analysis (CFA) model and its corresponding exploratory structural equation model (ESEM): A three-factor example (adapted with permission from Marsh, Liem, Martin, Nagengast, & Morin, 2010). Note: For clarity purposes, error terms of manifest variables (items) are not shown

and highly correlated latent factors that could potentially lead to serious multicollinearity and suppression effects such that the effects of the individual factors in predicting outcome measures are distorted in regression or SEM analyses. Although the MES-HS evinced robust psychometric properties (i.e., sound CFA factor structure, substantial factor loadings, excellent model fit) and sufficient evidence for the multidimensionality and distinctiveness of the motivation and engagement factors in the Wheel, the correlations amongst MES factors based on CFA solutions were relatively high (see e.g., Martin, 2007, 2009). Marsh and his colleagues (2010) asserted that part of the problem lies in the overly restrictive independent cluster models of CFA (ICM-CFA) in which items are required to load on one, and only one, latent factor, with non-target loadings constrained to be zero (see e.g., measurement components in Figure 1). The application of exploratory structural equation modeling or ESEM – an integration of CFA and SEM – is proposed to resolve this methodological issue in that in ESEM items are allowed to load on different latent factors specified in the measurement model. Further, the ESEM framework has a range of advantages inherent in the typical CFA/SEM including, for example, access to standard errors, goodness of fit, comparisons of competing models, assessment of between-group measurement invariance, and inclusion of correlated uniquenesses (Marsh et al., 2010).

Given the methodological benefits of ESEM, Marsh, Liem, Martin, Nagengast, and Morin (2011) adopted this technique to analyse responses to the MES-HS of 7,420 high school students and juxtaposed the results with those of CFA (see Figure 8 for comparison between CFA and ESEM models). The analyses, conducted using *Mplus* (Muthén & Muthén, 1998-2010), showed that although all the factor loadings were significant and substantial in both ESEM and CFA solutions, the 11-first-order factor in ESEM (CFI = .977, NNFI = .958, RMSEA = .025) suggested an overall better fit than its CFA counterpart (CFI = .935, NNFI = .928, RMSEA = .033). Further, the CFA factor correlations, ranging between r = -.70 and r = .70 (|M| = .40, SD = .22) tended to be systematically larger than the ESEM factor correlations, ranging between r = -.33 and r = .38 (|M| = .17, SD = .11). Thus, for example, the negative correlation between valuing and disengagement was r = -.70 in the CFA solution but r = -.33 in the ESEM solution. Importantly, ESEM also showed that the means of item loadings on their respective *a priori* factors (i.e., target loadings) were more substantial than their loadings on other factors (i.e., non-target loadings). Taken together, relative to CFA, ESEM provided stronger evidence for the multidimensionality of motivation and engagement constructs and the discriminant validity of the multiple factors in the MES-HS that are particularly useful to obtain more accurate beta parameters when these factors are jointly used to predict outcomes (e.g., achievement). Further, ESEM has also been evidently useful in showing acceptable fit indices of a big-five personality instrument which would typically fit poorly to the data within the CFA framework (Marsh et al., 2010). Beyond the use of ESEM to assess internal structure of a measure (Marsh et al., 2010, 2011), this technique can also be applied to examine structural relationships amongst latent factors to address substantive issues in educational psychology (see e.g., Marsh, Nagengast, Morin, Parada, Craven, & Hamilton, 2011, for the use of ESEM in bullying and victimization issues). ESEM appears to be a promising technique that educational psychology researcher can effectively harness to address the complex relationships of psycho-educational factors in their research.

METHODOLOGICAL ADVANCEMENTS AND FUTURE MODELLING POSSIBILITIES

The studies described above have illustrated some of the fundamental applications of CFA and SEM in addressing applied and substantive issues in motivation and engagement. There are, however, some recent notable methodological developments in latent variable modeling that offer important avenues for educational and psychological researchers in advancing interpretations of their data, proposing sounder and more compelling implications of their findings, and solidifying contributions of their research to the educational and psychology literature. In this section we highlight four of these major advanced techniques (i.e., composite-score latent modeling, cross-lagged latent modeling, latent variable interaction, and latent growth modeling) that are potentially important in advancing our understanding of student motivation and engagement.

Composite-score latent modeling. Latent variable modeling is known as a quantitative technique that requires a large sample size, with the recommended ratio of the number of parameters estimated and the number of cases that is at least 1:5 to obtain stability of estimated parameters (Iocobucci, 2010). In many instances, however, researchers are potentially limited by their relatively small sample size. For example, based on a sample of 249 high school students, Liem, Ginns, Martin, Stone, and Herrett (2012) tested a relatively complex model that assessed the effects of academic personal best (PB) goals – target performance standards that match or exceed a student's previous best – on various academic (deep learning, academic buoyancy, and academic flow) and social (positive teacher relationships and attitudes toward peer cooperation) outcomes at two time points. Given the 66 manifest variables involved the hypothesized model, the number of parameters to be estimated in their study can be up to 2,211. To redress this methodological problem, Liem and his colleagues (2012) employed composite-score latent modeling (Holmes-Smith & Rowe, 1994; Rowe & Hill, 1998). This technique markedly reduced the number of parameters because, rather than being predicted by its a priori manifest indicators, each latent factor in their model was defined by a weighted composite score derived from a confirmatory, one-factor, congeneric model (performed with a syntax provided by Raykov, 2009). Proportional factor score regression weights (κ) generated from a congeneric model solution were then used to modify the weight of each item before a composite score was calculated. Moreover, the number of parameters in composite-score latent modeling was further reduced as the factor loading (λ) and measurement error variance (θ) of each latent variable in the model were fixed with the values calculated using the weighted composite score reliability (ρ or rm - maximized reliability) of the corresponding factor. Whilst researchers dealing with such a situation would typically rely on a path analytic technique that does not purge constructs of measurement errors and disregards individual item or manifest variable contributions to their factor's composite score, Liem and colleagues (2012, p. 229) concluded that composite-score latent modeling (Holmes-Smith & Rowe, 1994) is "methodologically more robust and consistent with the essence of latent modeling as it takes into account item unreliability and unique (unequal) contributions to the composite score of the target factor, and hence, generates more accurate parameter estimates that are vital in understanding the effects of the key predictors of interest (e.g., PB goals) on a diverse range of outcomes." Composite score latent modeling is thus another application that can be useful under certain circumstances.

Latent factor interactions. We also note various research designs in which latent variable modeling as a quantitative technique offers methodological benefits in making sense of substantive data and advancing understanding of student motivation and engagement. One of these is pertinent to tests of interaction effects which have rarely been carried out in the context of latent variable modeling (Tomarken & Waller, 2005). This is surprising given that many theoretical models in educational psychology (e.g., aptitude-treatment interaction, Cronbach & Snow, 1977; expectancy-value model, Wigfield & Eccles, 2000) explicitly posit the role of interaction effects in educational outcomes. Recent methodological advancement allows researchers to assess the effects of interaction of latent factors on outcomes (see e.g., Nagengast, Marsh, Scales, Xu, Hau, & Trautwein, 2011). With measurement errors controlled, interactions of latent factors are expected to show more reliable and larger effects which are otherwise small and not easily detectable (Marsh, Hau, Wen, Nagengast, & Morin, in press).

Causal ordering. The classic cross-lagged panel analysis (Crano, Kenny, & Campbell, 1972) is viewed to be a crucial framework that sheds light on the relative salience of motivation and engagement in predicting subsequent achievement, and *vice versa*. In the context of latent variable modeling, motivation and achievement can be represented by latent factors that purge unreliability of measurement such that more accurate predictive paths between motivation, engagement, and achievement can be obtained. Liem, Martin, and Marsh (2011), for example, conducted a series of cross-lagged analyses and found that Time 1 adaptive cognition, Time 1 adaptive behaviour, and Time 1 maladaptive behaviour (negatively) showed a stronger pattern of predictive paths in predicting Time 2 achievement than Time 1 achievement predicting each of these motivation and engagement dimensions, pointing to the salience of motivation and engagement dimensions over achievement. In relation to the sustained benefits of motivation and engagement over time, there is a need to assess the development of students' motivation and engagement across their academic trajectory (see below).

Latent growth modeling. A powerful means to assess changes in motivation and engagement over time is latent growth modeling (Curran & Hussong, 2003; Tomarken & Waller, 2005) which is useful in, for example, developmental or time-based changes of students' motivation and engagement through high school years and how these changes relate to their achievement. Gottfried and colleagues (2009), for instance, performed a conditional latent growth modeling to assess how parents' motivational practices – measured when their children were at the age of 9 – were related to the children's intrinsic motivation in maths and science at the ages of 9, 10, 13, 16, and 17. The results showed that parents' task-intrinsic practices (i.e., parental encouragement of children's pleasure and engagement in the learning process) were beneficial for their children's intrinsic motivation at age 9 and its decline through age 17, highlighting the importance for parents to employ appropriate ways of motivating their children early.

CONCLUSION

The present chapter has presented a diverse range of research studies that illustrate the flexibility and versatility of confirmatory factor analysis (CFA) and structural equation modeling (SEM) as two major groups of latent variable modeling techniques that can effectively be used to address substantive and applied issues in motivation and engagement research. Alongside these more widely used applications, recent methodological developments (e.g., exploratory structural equation modeling [ESEM], multilevel CFA and SEM) provide researchers powerful tools to model the complexity of the relationships amongst the multitude of factors relevant to educational outcomes. Further, assessing effects of latent variable interactions, employing a cross-lagged panel design in the context of latent variable modeling, and harnessing latent growth modeling to complement repeated-measure design are promising areas in which latent variable modeling can further contribute to the theorizing and research in educational psychology. Aligned with the principle of methodological-substantive synergies (Marsh & Hau, 2007), educational psychology researchers are now in a stronger methodological position in seeking to address important applied and policy issues that aim to promote educational outcomes.

NOTE

[i] In evaluating the fit of the data to alternative models tested, a range of goodness-of-fit indices were assessed. Following recommendations by Marsh, Hau, and Wen (2004), the Comparative Fit Index (CFI), the Non-Normed Fit Index (NNFI), the Root Mean Square Error of Approximation (RMSEA), the χ^2 test statistic, and an evaluation of parameter estimates were used in the present chapter to assess model fit. The RMSEA index is less affected by sample size than the χ^2 test statistic and values at or less than .08 and .05 are typically taken to reflect acceptable and excellent fit, respectively (Marsh, Balla, & Hau, 1996; Yuan, 2005). The NNFI and CFI vary along a 0-to-1

continuum in which values at or greater than .90 and .95 are typically taken to reflect acceptable and excellent fit to the data, respectively (McDonald & Marsh, 1990). The CFI contains no penalty for a lack of parsimony so that improved fit due to the introduction of additional parameters may reflect capitalization on chance, whereas the NNFI and RMSEA contain penalties for a lack of parsimony (Yuan, 2005).

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10. LINKING TEACHING AND LEARNING ENVIRONMENT VARIABLES TO HIGHER ORDER THINKING SKILLS: A STRUCTURAL EQUATION MODELING APPROACH

INTRODUCTION

Studies of learning environments, particularly during the past 30 years, have rapidly drawn the interests of educational researchers and theorists. In recent decades, studies of learning environments have been concerned with conceptualization and theory development (Bryk & Raudenbush, 1992). Student ratings have also been traditionally included in faculty and course evaluation in higher education settings. Research on learning environments (Astin, 1993; Fraser, Walberg, Welch, & Hattie, 1987; Fullerton, 2002) show that psychosocial characteristics of classroom learning environments demonstrate incremental validity in predicting student achievement. These psychosocial characteristics are useful in curriculum evaluation studies, and can provide teachers with useful information to arrange more optimally functioning classrooms.

Constructivist-based, personal forms of learning environment measures designed to tap students' individual, rather than collective perspectives of classroom life have also been developed (Cavanagh, Dellar, Ellett, & Rugutt, 2000; Fraser, Fisher, & McRobbie, 1996; Rugutt, Ellett, Culross, 2003). Learning environment has often been studied for the purposes of ensuring maximum student achievement in his/her education endeavors. Further, learning is a highly individual process which occurs within a larger environment. Learning is thus mediated by an individual's interactions with and perceptions of the external environment (Loup, 1994; Olivier, 2001).

It has been shown that the surrounding teaching and learning environments or institutional culture influences educational behaviors of their students, faculty or staff (Astin, 1993; Holland, 1997; Tinto, 1993). Research has shown that academic environments contribute to gain in student abilities, interests, and attitudes (Feldman, 1988; Feldman, Ethington, & Smart, 2001). Holland (1997) noted that the environments foster the development of competencies, motivate people to engage in different activities, and reward people for their display of values and attitudes. Environment therefore influences personal and professional self-perceptions, competencies, attitudes, interests, and values. Holland (1997) further indicated that college students experience includes but not limited to; (a) a student's search for academic environments that match their patterns of abilities,

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 217–239.

interests, and personality profiles; (b) effects of academic environments on student's social behavior in an effort to acquire the desired abilities, interests and values; and (c) a student achievement to include a function of personality type and the academic environment.

FRAMEWORK

Most research has focused on student and faculty interactions in the classroom context. However, few studies have examined the linkages among student learning environment teaching and learning variables such as higher order thinking skills, self-efficacy, motivation, student-faculty interaction outside of classroom, and student involvement in learning (collaborative and self-directed learning). Investigating factors that influence student learning processes as well as determining whether faculty or the student have an impact on student overall academic performance are important professional issues.

Additionally, it is important to consider student's involvement in learning (e.g., cooperating with other students when doing assigned work and on class activities, knowing other students, learning from other students in class, and working with other students in class), as it plays a key role in student's higher order thinking skills as well academic achievement. Since faculty provides the student with learning materials, the student has a responsibility of completing the required activities so as to realize an improved understanding of the subject matter.

PURPOSE OF THE STUDY

The primary purpose of this study was to develop an empirically derived, structural equations model to broaden our understanding of a complex, theory-based set of personal and organizational factors that contribute to higher order thinking skills. The study explored the degree of influence student-faculty interaction, motivation and self-efficacy has on student's development of higher order thinking skills. Specifically, the study focus was three-fold: 1) to investigate interrelationships existing between teacher student relations (TSR), self-efficacy (SE) and motivation (MO). 2) To investigate the direct relationship between; a) teacher student relations and higher order thinking skills (HOTS); b) self-efficacy and higher order thinking skills; and c) motivation and higher order thinking skills. 3) To use confirmatory factor analysis to validate all the study variables (MO, SE, TSR, HOTS).

SIGNIFICANCE OF THE STUDY

This research is important since it integrates student teaching and learning variables that can impact academic achievement. While numerous studies have focused on student-faculty interaction, and the impact it has on student academic performance, fewer studies have investigated linkages existing among the teaching and learning variables such as higher order thinking skills, self-efficacy, student-faculty interaction, student involvement in learning and motivation. Further, this study is important since factors outside the classroom environment are studied to determine if they also play a role in student's development of higher order thinking skills.

RATIONALE FOR STRUCTURAL EQUATION MODELING (SEM)

Like many multivariate statistical techniques, the use of SEM may be well grounded, but many aspects of SEM are yet to be understood and embraced by most researchers and consumers of research reports. As such, it is important that researchers continue to share their findings on the design, modeling, and recent SEM developments in a bid to expand and advance knowledge in this important research area. The multi-step approach that is completed in SEM, particularly the measurement and structural model, make SEM a versatile tool for a variety of statistical analyses including instrument development and validation as well. Use of confirmatory factor analysis (CFA), a structural equation modeling (SEM) technique in education has gained prominence in recent years, particularly in scale development and data analysis. Noar (2003) posit that "CFA has taken on a pivotal role in the development of quantitative scales, although there is little literature that discusses the unique contribution that CFA brings to measurement development, and the process by which it is employed " (p. 623). In quantitative data analysis, multiple linkages among study variables are investigated using SEM technique. The CFA approach "offers a strong analytical framework for evaluating the equivalence of measurement models across distinct groups" (Brown, 2006, p. 49).

PRIOR RESEARCH

Motivation and Higher Order Thinking Skills

The literature regarding the relationship between motivation and higher order thinking skills is drawn from diverse settings such as K-12 education, higher education, and even training to become military air traffic controllers. In few cases, motivation is viewed as the dependent variable with higher order thinking skills as an independent variable. More often, motivation is viewed as a predictor of higher order thinking skills. Teacher as a motivation factor influence students' learning greatly. How teachers behave in classroom can directly promote student learning and motivation. It is important that teachers care about how they motivate students because if the students are not actively motivated to learn, learning will not occur.

Patrick, Hisley, Kempler, and College (2000) noted that teacher behaviors promote student intrinsic motivation to learn. Their research of how teachers' enthusiasm and interaction relate to each other found a significant relationship between teacher-student relations and intrinsic motivation. Students who are intrinsically motivated view learning as a goal in itself, while students who are extrinsically motivated view learning as a reward (Cokley, 2000; Covino, & Iwanicki, 1996; Dweck, 1986). Donohue and Wong, (1997) studied motivation while Nastasi and Clements (1994) studied motivation and higher order thinking in third grade students in two cooperative computer environments, one using Logo for programming and the other using computer based instruction for writing. They found that the treatment (environment) accounted for significant portions of the variance in both motivation and in higher order thinking skills and that motivation accounted for a significant portion of the variance in higher order thinking skills. While this study treated higher order thinking skills as the dependent variable, the authors maintained that the learning environment that placed greater emphasis on higher order thinking skills saw higher levels of student motivation. DiCintio and Stevens (1997) investigated whether the level of higher order thinking required by instruction is related to motivational goals. Higher order thinking skills were found to be a significant predictor of motivational variables with fifth grade providing more emphasis on higher order thinking skills than sixth and seventh grade mathematics classes and much more emphasis on higher order thinking skills in a high ability fifth grade class than in an average ability fifth grade class. The motivational variable of mastery orientation (intrinsic motivation) was also significantly higher for fifth graders than for the older students in the study. The authors, however, cited a lack of variance in higher order thinking skills within grade level as a confounding issue limiting generalization of the study's conclusions.

Kanfer and Ackerman (1989), studied of skills acquisition among U.S. air force recruits learning to become air traffic controllers found that goal assignments provided during the declarative stage of complex skill acquisition actually decreased performance among both low-ability and high-ability groups with more impairment among low-ability subjects. They define the declarative phase as the earliest phase of skill acquisition when the focus is on facts. This stage is followed by stages of integration and automatization of the skill. Higher order thinking skills are most closely related to the integration phase of skill acquisition. The study concludes that low-ability subjects benefit more from imposition of a goal assignment (motivation) during the integration portion of complex skill acquisition than do high-ability subjects. Their conclusion can be stated another way, that emphasis on higher order thinking skills provides an environment in which motivational interventions are more effective. While learning to become an air traffic controller certainly differs from academic learning in a university setting, Kanfer and Ackerman's (1989) study is one of few to consider the effect of emphasis on higher order thinking skills on motivation rather than vice versa.

Other studies that have investigated the relationship between motivation and higher order thinking skills with mixed results include research by Singh and Singh (1994) on the role of motivation in integrational capacity in young children. They found that motivation was a significantly better predictor of integrational capacity than an ability construct was for some but not all age levels. Prediction models presented in these studies varied by ethnicity and by gender. However, Plecha (2002) found no significant difference in negative impact on students' motivation and achievement based on negative teacher-student relationship.

Self-efficacy

Self-efficacy, defined as "beliefs in one's capacity to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3) has guided researchers for over a quarter of a century. The beliefs of self-efficacy have been identified as a factor that may contribute to the success or failure of an individual with respect to specific tasks. Self-efficacy reflects a person's level of confidence in their ability to perform a behavior to produce specific outcomes. It is believed to affect the choice by an individual to take on certain tasks and influences the amount of effort and persistence needed to succeed (Bandura, 1977; Schunk 1985).

Bandura's work has shown that there is considerable evidence that self-efficacy (SE) beliefs play a strong role in human behavior. Self-efficacy plays an important mediating link between cognition and behavior and has been viewed as highly situational and consists of competency and motivational factors that subsequently affect an individual's ability to organize and execute courses of action required to attain various types of goals and performances (Bandura, 1997). Further, personal perceptions of efficacy and resulting actions are influenced by factors in the environment (Ellett, Loup, Culross, McMullen & Rugutt, 1997). Ellett, 1995 and Ellett, 2000 study has shown predictable relationships between child welfare staffs= self-efficacy beliefs, strength of motivation and persistence, and intentions to remain or leave employment in child welfare.

High self-efficacy beliefs have been shown to enhance motivation, promote higher goal-setting behaviors, and influence persistence and commitment to goal accomplishment (Bandura & Schunk, 1981). Loup (1999), Loup and Ellett (1993), Loup, Clarke, Ellett and Rugutt (1997) present self- and organizational efficacy assessment measures for use in schools to assess personal motivational elements of the efficacy construct in terms of effort and persistence put forth to achieve specific goals. The measure contextualized self-efficacy behavior by requiring respondents to consider the particular context (such as school, classroom) in which specific goals might be achieve. There have been few studies (Ellett, Loup, Culross, McMullen, & Rugutt, 1997) that have been conducted using the self-efficacy construct as it relates to student learning in higher education settings.

Student-faculty Interactions

Other studies have found that students who frequently interacted with faculty had greater satisfaction with their college experiences as compared to students who interact at a lesser level (Wilson, Gaff, Dienst, Wood, & Bavry, 1975). Students who interacted more frequently with faculty, performed better academically than students who seldom met with the faculty (Pascarella & Terenzini, 1976; Pascarella, Terenzini, & Hibel, 1978). These findings strongly indicate that student-faculty interactions are important to a student's college academic performance. Tinto (1987, 1993) as well as Woodside (1999) concluded that both informal and formal interaction with teachers is important in predicating freshmen academic outcomes, satisfaction, and attrition.

Some factors that are associated with student-faculty interaction include; student's academic achievements, educational attainment and aspirations, career and major choice, college satisfaction and persistence, and cognitive development. First-year students have occasional contact (once or twice a month) with their instructors, while seniors at doctoral-extensive universities interacted less with faculty members than first-year students at liberal arts colleges, (Kuh, 2001). Pascarella and Terenzini (1976, 1991) pointed out that the frequency of student-faculty interactions significantly predicts freshman academic outcomes such as college satisfaction and attrition. Students learn how experts (mentors) think and solve problems by interacting with faculty members inside and outside the classroom (Institutional Benchmark Report, 2002). Numerous projects have focused on the relationship that exists between student-faculty interactions and outcome variables such as academic achievement and overall satisfaction of college students (Astin, 1993; Kuh, 2001; Terenzini & Pascarella, 1994).

METHODOLOGY

Research Design

This study is both cross-sectional and survey in nature. It is cross-sectional in that it focuses on major variables of higher education teaching and learning environment at a specific period. It is also a survey research design because the students were surveyed on key variables of teaching and learning environment. Further, a post hoc correlation design was used as a framework for data analysis in the study. Thus relationships among the variables was explored (rather than manipulated) in an attempt to develop a structural equation model for examining linkages among key variables of the study.

Measures

A variety of self-report measures have been developed to examine student perception of learning environment and their own characteristics as learners. This study used measures contained in *Student Assessment of Teaching and Learning (SATL) (Short-Form)*, first developed by Ellett, Culross, McMullen, and Rugutt, (1996), and later revised by Ellett, Loup, Culross, McMullen and Rugutt (1997). The measures assessed a wide variety of factors among college students.

Motivation (MO). Mayer (1998) found that motivational skills were necessary in academic problem solving but cognitive and strategic (metacognitive) skills were even more necessary while House (1995) found that motivational variables were significant predictors of grade performance but that academic background was a stronger predictor. For this study, student motivation (MO) is comprised of five statements. Students respond to the degree to which various activities enhanced their learning using a three point scale as follows: 1 = learning not enhanced, 2 = learning sometimes enhanced, 3 = learning almost always enhanced. A complete list of the five statements making up the MO construct is found in Appendix A.

Higher Order Thinking Skills (HOTS). Resnick (1987) indicates that HOTS is a complex construct to be given a precise definition but instead lists nine features that collectively sum up what HOTS entail. Rugutt and Chemosit (2009) define HOTS as cognitive characteristics that enable a student to analyze and reason toward an informed response in a variety of scenarios. HOTS, nearly synonymous with critical thinking (Bean, 2001), develop with a student's active participation and involvement in the educational process (Kaplan & Kies, 1994). Ennis (1985) argues that critical thinking is the practical side of developing one's HOTS, while Pascarella (1989) specifies that one's critical thinking ability develops in terms of his or her ability to reason and evaluate information. HOTS differ from knowledge because they are cognitive abilities rather than the retention of specific information. HOTS, then, develop independent of a given curricula while knowledge may or may not transfer across situation. Cognitive growth occurs as one develops HOTS or critical thinking skills. For this study, the variable for classroom emphasis on higher order thinking skills (HOTS) is comprised of 4 statements (see Appendix A). Students rate the amount of emphasis given to each type of learning as follows: 1 = no emphasis, 2 = some emphasis, 3 = much emphasis, 4 = very much emphasis.

Self-efficacy (SE). The vast majority of studies of learning environments have occurred in the K-12 context in schools and at the classroom level. There have been some past efforts to focus research on the study of college/university environments (Astin, 1993; Kuh, 2001; Kuh, & Hu, 2001; Pace & Stern 1958; Stern, 1970; Pascarella, 1980, 2001). Astin (1993) posit that "student-faculty interaction had a significant positive correlation with every academic attainment outcome: college GPA, degree attainment, graduating in honors and enrollment in graduate or professional school" (p. 383). Student-faculty interaction also had positive effect on student intellectuals and personal growth, behavioral outcome and career outcome. Pascarella and Terenzini in (Woodside, 1999) point out that the frequency of student-faculty interactions significantly predicts freshman academic outcomes such as college satisfaction and attrition. Student-faculty interaction produces a sense of identification with faculty and has important implications for student development (Astin 1993; Lamport, 1993). For this study, self-efficacy construct comprised of responses to 4 statements. The four items comprising the self-efficacy measure are shown in Appendix A. Students respond to the amount of effort or effort and persistence they put forth to enhance their own learning on a scale of 1 = little or none to 5 = a large amount.

Teacher Student Relations (TSR). Tinto (1987, 1993) stated that student-faculty interactions, which include both formal classroom experiences and informal interactions out of class, are crucial to the academic continuation and intellectual development of students. According to Tinto (1987, 1993), a lack of such interactions is a significant determinant of attrition. One project that specifically examined the relation between student-faculty interaction and academic performance found that student-faculty interactions had a significant influence on students' academic performance as measured by students' SAT scores and freshman year cumulative GPA. The interactions were most powerful in affecting achievement if they concerned intellectual or course-related subjects. It was also found that students who interacted more frequently with faculty performed better academically than what was predicted from their SAT scores. On the other hand, students who seldom met with faculty tended to achieve at lower levels than predicted. Taken together, the existing research suggests that student-faculty interactions are important to a student's college experience (Astin, 1993; Pascarella & Terenzini, 1991; Woodside, 1999). The five items comprising the teacher-student relations measure are shown in Appendix A. For this study, TSR construct comprised of 5 items where students rate the amount of emphasis given to each type of classroom activity as follows: 1 = almost never to 5 = almost always.

The results of the exploratory factor analysis (EFA) and reliability analyses are reported in the next section. The subscales of the instrument, items for each scale and their corresponding Cronbach alpha reliabilities are presented in Table 1.

TARGET POPULATION FOR THE STUDY

Sampling

The sample for this study consisted of 2,190 students from 145 classes in the Evening School of the Division of Continuing Education at one large southern university. During the semester, the sampled students took a variety of courses in such topic areas as mathematics, natural science, social science, and humanities. They also represent a broad array of individuals, including traditional-aged, nontraditional-aged, differing employment status, and gender. This sample was 40% male, 60% female; 60% not employed full-time; 69% were traditional students while 31% were non-traditional students.

DATA ANALYSES

Once data collection procedures and the construction of various data files was complete, a variety of analyses were completed that included, descriptive statistics for the sample, a series of exploratory Principal factor analysis using Promax rotation was conducted to identify empirically derived dimensions of the study measures, reliability analyses for each measurement dimension, Confirmatory Factor Analysis (CFA) to operationalize the measures, goodness of fit indices for the measurement model, structural equation modeling (SEM), and fit statistics for the structural model to understand linkages among the latent variables using LISREL (Jöreskog & Sörbom, 1996). Measured variables were selected from the larger measures contained in *Student Assessment of Teaching and Learning (SATL) (Short-Form)*, first developed by Ellett, Culross, McMullen, and Rugutt, (1996), and later revised by Ellett, Loup, Culross, McMullen and Rugutt (1997) (with permission). The correlations and covariance matrices calculated using SPSS (SPSS, Inc., 1990) were used as input into LISREL (Jöreskog, & Sörbom, 2003) to develop the Structural Equation Model (SEM). Individuals comprising the undergraduate college students were used as the units of analysis.

Table 1 Student Assessment of Teaching and Learning (SATL) (Short-Form)

Item	Construct and Item Description	Cronbach Alpha Coefficient
	Motivation (MO)	0.88
mo1	The instructor's enthusiasm for teaching, learning and the subject taught	
mo2	The interpersonal climate in the classroom (e.g., patience, courtesy, respect)	
mo3	Encouragement for students to express their own ideas	
mo4	Encouragement for students to participate in discussions	
mo5	Encouragement for students to ask questions	
	Teacher Students Relations (TSR)	0.93
tsr1	The teacher takes a personal interest in me	
tsr2	The teacher considers my feelings	
tsr3	The teacher helps me when I have trouble with the work	
tsr4	The teacher talks with me	
tsr5	The teacher moves about the class to talk with me	
tsr6	It is alright for me to tell the teacher that I do understand	
tsr7	The teacher's questions help me to understand	
	Self-efficacy (SE)	0.80
se1	How much effort did you put forth in this course to enhance your own learning?	
se2	When there were difficult or uncertain obstacles to overcome in learning/achieving in this course, how much effort and persistence did you put forth to enhance your own learning?	
se3	How much knowledge and/or ability do you think you have to accomplish your learning objectives in college?	
se4	How much personal responsibility do you think you have to accomplish your learning objectives in college?	
se5	How much success do you think you have had in accomplishing your learning goals in college?	
	Higher Order Thinking Skills (HOTS)	0.93
hots1	Learning factual information	
hots2	Developing concepts	
hots3	Understanding and applying principles and rules	
hots4	Understanding and applying theories	
hots5	Critical analysis and/or problem solving	

Exploratory factor analysis (EFA). EFA focuses on finding structures or patterns of correlations in data and this technique is most often used in the early stages of instrument development (Vogt, 2007). For the current study, a series of Principal factor analysis using Promax rotation was conducted on the exploratory sample for the four study measures (HOTS, SE, MO, TSR) to identify measurement sub constructs as defined by the magnitude and patterning of item loadings on extracted components (correlations). This study randomly divided the full sample (n = 2190) into two samples for analysis. A smaller sample (n = 800) was analyzed using exploratory factor analysis (EFA) and for generating the Crobach alpha reliability coefficients for the four instrument subscales (see Table 1). The other portion (n = 1390) was used for the confirmatory factor analysis (CFA) methods. The splitting of data and running two separate analyses were important in the validation of the study latent constructs since the second sample acted as a validation sample. CFA requires larger sample sizes than exploratory analyses because of the large number of parameters it evaluates given the model described in this study. Principal factor analysis using Promax rotation was conducted on the exploratory sample.

Structural equation modeling (SEM) analyses. Latent variable structural equations modeling (SEM) is an appropriate procedure for use with non-experimental data (Keith, 1998; Quirk, Keith, & Quirk, 2002). This procedure performs a confirmatory factor analysis (CFA) and path analysis simultaneously (Keith, 1997; Marsh, 1994). In this study, developing a SEM to best represent the data required two key steps, the measurement model and the structural model. There are several basic steps that are involved in setting up a SEM model. Some of these steps have been discussed in detailed in Kline (2005), in scaling procedures research and in SEM books (e.g., Brown, 2006; DeVellis, 1991; Jackson, 1970; Maruyama, 1998; Netemeyer, Bearden, & Sharma, 2003). These steps include: a) use of literature and theory in the development of latent constructs as well as linkages among study variables; b) determining whether the model is identified, that is the difference between the number of freely estimated model parameters and the number of pieces of information in the input variance-covariance matrix; c) selection of measures and data preparation; d) data analysis; e) model re-specification; and f) description of the analysis and writing of reports. Researchers interested in details of the above steps should consult the above resources as well as other works in SEM techniques.

First, the measurement model was specified by completing a CFA of the study variables and computing goodness of fit statistics for each of the four latent variables (study measures). Subsequently, a two-step LISREL approach was used to further simplify and operationalize the measured variables used in developing the SEM and to generate goodness of fit statistics to determine the adequacy of the measurement and structural models.

RESULTS

Descriptive Statistics

For the Higher Order Thinking Skills (HOTS) measure, item means ranged from a low of 3.12 ("Critical analysis and/or problem solving") to a high of 3.31 ("Developing concepts") on a scale of 1 to 4. For the Self-efficacy (SE) measure, item means ranged from a low of 4.03 ("When there were difficult or uncertain obstacles to overcome in learning/achieving in this course, how much effort and persistence did you put forth to enhance your own learning?") to a high of 4.33 ("How much personal responsibility do you think you have to accomplish your learning objectives in college?") on a scale of 1 to 5. For the motivation (MO) measure, item means ranged from a low of 2.51 ("The extent to which students are involved") to a high of 2.71 ("Clarification of content/ideas when confusion exists") on a scale of 1 to 3. For the Student-faculty interaction (TSR) measure, item means ranged from a low of 3.32 ("The teacher moves about the class to talk with me") to a high of 4.15 ("It is alright for me to tell the teacher that I do understand") on a scale of 1 to 5.

Structure of Measures

Confirmatory factor analyses of the four measures (see Appendix A) identified the following subscales for the various measures used in this study: higher order thinking skills (HOTS), self-efficacy (SE), motivation (MO) and teacher student relations (TSR). The results of the CFA led to revision of the number of items per subscale as presented in Table 1 to those presented in Appendix A. Table 2 shows the LISREL path coefficients among the various measures.

Table 2. Path Coefficients of Figure 1 for the Study Latent Variables: Higher Order Thinking Skills, Self-efficacy, Motivation and Teacher Student Relations

Variables	MO	TSR	SE	HOTS
MO	1.00			
TSR	0.60*	1.00		
SE	0.50*	0.35*	1.00	
HOTS	0.37*	0.25*	0.40*	1.00

*Note: * p< 0.05: Significant at 0.05; HOTS: Higher order thinking skills; SE: Self-efficacy; MO: Motivation; TSR: Teacher student relations*

Fit Statistics for the Measurement Model

To evaluate goodness of fit of the model the goodness of fit index (GFI) and the root mean square residual (RMR) (Marsh & Bala, 1994; Marsh, Bala, & Hau, 1996; Marsh, Bala, & McDonald, 1998), among others, were used. The root mean square error of approximation (RMSEA) index was also used because the GFI and

RMR indices do not take into account the number of parameters estimated in the model, and the model goodness of fit improves as the number of estimated parameters increases.

Table 3 includes the chi-square values (x^2) with associated degrees of freedom (*df*), root mean square error of approximation (RMSEA), normed fit index (NFI), comparative fit index (CFI), root mean square residual (RMR), and goodness of fit (GFI) index values for each variable in the measurement model and in the structural models. The results for the model's goodness of fit indices were within acceptable limits (Bentler, 1993; Brown & Cudek, 1993; Byrne, 1989, 1993, 1998; Diamantopoulus & Siguaw, 2000; Schumaker & Lomax, 1996). The allowable fit values for the NFI, CFI and GFI indices are those close to 1.00. For RMSEA values less than 0.08 are considered acceptable, and RMR values as close to zero as possible are preferred. The results shown in Table 3 support a good fit of the variables to the measurement and structural models.

Table 3. Summary of hypothesized measurement model fit statistics for each study variable

Measurement	χ^2	df	GFI	NFI	RMR	RMSEA
Higher Order Thinking skills	4.16	2	1.00	1.00	0.009	0.020
Self-efficacy	2.68	2	1.00	1.00	0.098	0.016
Motivation	13.87	2	0.97	0.98	0.024	0.065
Teacher Student Relations	15.23	2	0.99	0.99	0.012	0.069
Structural Model						
HOTS (Dependent Variable)	431.40	113	0.93	0.98	0.044	0.036
Independent Variables (MO, TSR & SE)						

Note: df: Degrees of freedom; GFI: Goodness of Fit; NFI: Normed Fit Index; RMR: Root Mean Square Residual; RMSEA: Root Mean Square Error of Approximation

Structural Equation Modeling Analyses

Figure 1 shows the CFA loadings for the measurement and the structural models. The conceptual focus guiding the development of the SEM was to develop a causal model to examine the influence of the motivation (MO) and teacher student relations (TSR) variables on the higher order thinking skills (HOTS) variable through self-efficacy (SE). The latent variables (ovals) are constructs inferred from the measured variables (indicators shown in rectangles) previously developed using CFA procedures. The paths from the latent variables (ovals) to the measured variables (rectangles) show the weighting (not included in the schematic but were all larger than 0.50 and significant) of the measured variables as they operationalize the latent variables (factor loadings). All the measurement factor loadings were significant indicating that the indicators were reliable measures of their respective latent constructs. Paths from the latent variable (SE, TSR, MO) to the HOTS (the structural model) are standardized regression coefficients that suggest the extent to which each independent variable relate to the dependent variable (HOTS). The curved lines and the double-headed arrow lines indicate bivariate correlations between the various latent variables (SE, MO and TSR). A disturbance (d_1) term is included in the model to represent influence on the latent variable HOTS other than those already contained in the model (MO, SE, TSR). The measured variables also take into account any error or other influences not shown (e.g., e_1, e_2, e_3 …) that may be influencing the variables beyond the latent variables. Separating error from the model enhances the interpretation of the constructs of interest and their effects on each other (Keith, 1998; Quirk, Keith, & Quirk, 2002). The various fit statistics that were used to judge the adequacy of the measurement and structural models are shown in Table 3 and they suggest that the models provided a good fit to the data.

Given an adequate fit of the model to the data, the next step was to interpret the paths. The path from self-efficacy (SE) to higher order thinking skills (HOTS) was 0.16 while the path coefficient from teacher student relations (TSR) to higher order thinking skills (HOTS) was 0.25. The path from MO to HOTS was 0.37. This path suggests that for each standard deviation increase in motivation, HOTS increased by 0.37 of a standard deviation. This means that motivation appears to have had a moderate, positive effect on HOTS. The path from TSR to HOTS was also positive and significant. The path suggests that for each standard deviation increase in teacher student relations, HOTS increased by 0.25 of a standard deviation. This means that teacher student relations variable appears to have had a moderate, positive effect on HOTS. Motivation, self-efficacy and teacher student relations demonstrated moderately strong, positive relationships to each other (MO on SE = 0.50; MO on TSR = 0.62; SE on TSR = 0.53). The three coefficients were statistically significant ($p<.05$). Standardized regression coefficients (path coefficients) are presented in Table 2. Where the path coefficient was significant at an alpha level of 0.05 (95% level of significance), a single asterisk was used. It should be noted that the path coefficients between any two latent variables presented in the figure are adjusted for the other latent variables in the model.

DISCUSSION AND IMPLICATIONS

The purpose of this study was to explore the degree of influence student-faculty interaction, self-efficacy and motivation has on student's development of higher order thinking. The results show that all the study variables (motivation, self-efficacy and teacher student relations) significantly predict higher order thinking skills. The path coefficients between motivation and self-efficacy, between motivation and teacher student relations and between self-efficacy and teacher student relations were positive and significant. All the path coefficients between the independent variables (MO, SE, TSR) and the dependent variable (HOTS) were positive and significant.

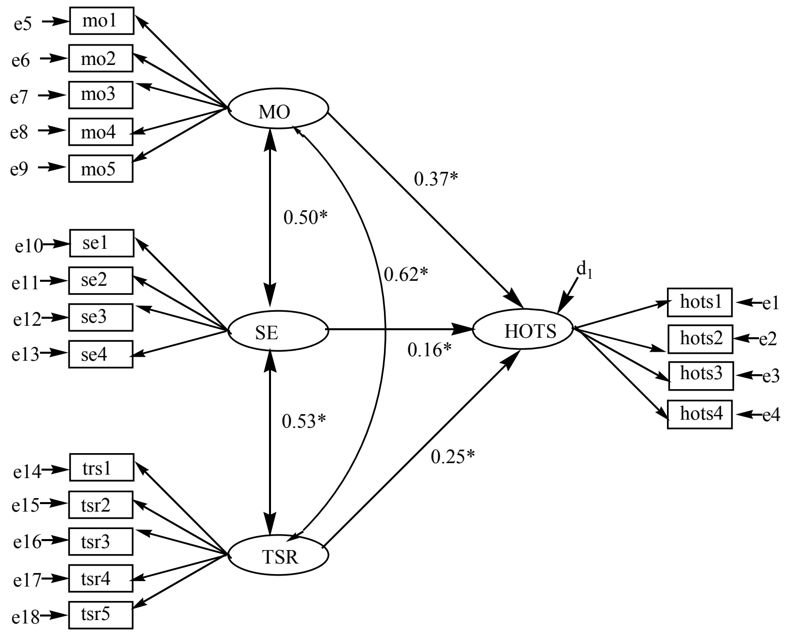

*Figure 1: Structural equation model (SEM) for study variables using the student higher order thinking skills as the dependent variable. Note: * p< 0.05; HOTS: Higher order thinking skills; EFF: Self-efficacy; MO: Motivation; TSR: Teacher student relations*

Implications for Higher Education and Practice

The study variables (higher order thinking skills and teacher student relations) have a rather rich history in the empirical and theoretical literatures pertaining to student-faculty interaction (Astin, 1993; Pascarella & Terenzini, 1991; and Tinto, 1993), discussion of motivation (Ames, 1992; DiCintio & Stevens, 1997; House, 1997; Plecha, 2002; Tavani & Losh, 2003), self-efficacy (Bandura, 1977, 1997; Bandura & Schunk, 1981) and investigation of development of higher order thinking skills (DiCintio & Stevens, 1997; Kanfer & Ackerman, 1989; Nastasi & Clements, 1994). Further, understanding individual and institutional factors related to student higher order thinking skills in learning are important professional issues. The results of this study clearly show that teacher student relations, self-efficacy, and motivation are important variables in predicting higher order thinking skills. Therefore, it seems important for institutions of learning and university faculty to be sensitive to the student-level and organizational characteristics. Leaders in various units of colleges and universities behoove them to be cognizant of the elements of higher order thinking skills, active learning strategies, teacher student relations, student motivation and self-efficacy so that they are fully involved in providing the kinds of educational experiences that can enhance the development of these important and affective higher order thinking characteristics in their learners. This strategy may lead to increase student motivation, student-faculty interaction, elevated active learning strategies and development of higher order thinking skills and thus student academic success. Strengthening these individual and institutional characteristics seems particularly important for learners and institutions of higher learning.

Implications for Theory Development

The network of relationships in the structural model in this study shows how higher order thinking skills is statistically, and importantly related to both the level of motivation as well as to the level of teacher student relations and self-efficacy beliefs about learning tasks of students. Further, the results of this study have implications for the continued development of a nomological network (Cronbach & Meehl, 1955) for a general theory of *motivation and learning, and higher order thinking skills in* institutions of learning and other organizations. This research approach and concern has been on studying linkages of factors related to higher order thinking skills. The researcher believes this approach to theory development will provide a conceptual framework for future research that has stronger implications for improving strategies used to motivate learners and thus improve student higher order thinking skills. Thus, a developing theory of motivation and learning and higher order thinking skills can be understood through the investigation of factors related to higher order thinking skills at institutions of higher learning. Obviously, there are a host of other organizational and personal variables that can be researched and added to the nomological network in explicating a theory of motivation and learning and higher order thinking skills. With this goal in view, this study and other recent studies in the fields of self-efficacy (e.g., Bandura, 1977, 1997; Astin, 1993; Tavani, & Losh, 2003; Tinto, 1993) will shed more light to the current research on predictors and correlates of higher order thinking skills.

Implications for Future Research

This study was completed at only one point in time with one large, institution sample of traditional and non-traditional students. Replications of the study, with the refined study measures resulting from the confirmatory factor analyses, and the addition of other important measures as well, are needed. This study synthesized pertinent studies in the areas covered by the study variables and thus produced greater benefits that augmented the statistical results. Majority of past research have made use of final grades and student success as indicators of good teaching, learning and student motivation. This study advocates for the need for learner-centered research that focuses on the cognitive aspect of all learners; how they learn, how learning might be increased, and what environmental factors can assist in achieving such improved results and motivation.

For the most part, the measures used in this study yielded reliable data, though some of the measurement dimensions may need to be refined with revisions of items. The researcher believes these measures are adequate to do replication studies in other large research/extensive institutions of higher learning, and with other research designs. The findings of this study suggest that these variables may be quite potent and yield rich information for theory development. As well, the continued use of mixed methodologies in future studies can strengthen the nomological network (Cronbach & Meehl, 1955) of a theory of higher order thinking skills and learning and add to the utility and explanatory power of the quantitative results presented in this study.

Since motivation consists not only of making student receptive to and excited about the subject taught, but also making them discern the value of learning itself (Covino, & Iwanicki, 1996), there are a number of strategies that are of value to the teacher in order to effectively motivate individual student or groups of students and lead them to the development of higher order thinking skills. First, through teacher student relations, the teacher gets to know students' preconceptions and misconceptions or subject matter, student's collaborative and active learning strategies such as student-to-student relations and how such relationships could further the learning process, students' areas of interests, student weak points, students' ability to learn factual information and to develop concepts, understanding and applying principles, rules, applying theories, and problem solving strategies among others. With this knowledge, the teacher can devise strategies to foster motivation and tickle the minds of students for the development of higher order thinking skills. Good and Brophy (1987) presented four areas such as supportive environment, as espoused in the elements of teacher student relations such as teacher taking a personal interest in student and student learning, considering student feelings, helping student when they are faced with trouble with work and maintaining frequent communication. A second strategy is to provide an appropriate level of challenge or difficulty as listed in the elements of motivation such as encouragement of students to participate in discussions, providing the kind and number of thought-provoking questions, encouragement of students to compare and contrast and compare ideas, encouragement of students to get involved in discussion among themselves, and encouragement of students to apply course content to solve problems or to understand real life situations. A third strategy requires that the teacher provides meaningful learning objectives so that the student remains encouraged in expressing their own ideas, participate in small and large discussion groups, compare and contrast ideas, and appreciate to learn from each other. The fourth strategy involves moderation and variation in strategy such as dividing a class time into a variety of activities such as lecture, small groups, large group projects and presentation, and discussion groups. Further, subjects such as mathematics and science courses are quite often best taught using a teacher-centered style where the students are taught a particular skill and then asked to duplicate that skill on their own until mastery. Social sciences and humanities often are exactly the opposite, opening up much greater opportunities for in-class discussions, group projects, and extended peer interaction and differential influence on motivation and development of higher order thinking skills.

The findings of this study call for continued research on correlates and predictors of higher order thinking skills. It must be acknowledged that there may be more variables affecting motivation, learning and development of higher order thinking skills that cannot be altered than those that can. Demographic, personality variables and family patterns, for example, may be the strongest predictors of motivation and thus higher order thinking skills but lend very little to manipulation. This is not to say that researching these alterable variables is useless because of their relatively small influence. Rather, as educators, our noble task is to seek to influence what we can. Based on the findings of this study, it is evident that a systematic evaluation of correlates and predictors of student motivation and thus higher order thinking skills at institutions of learning requires multi-method and multi-measure approaches to the analysis of higher order thinking skills. Although the results of this study may not generalize to other universities, they are expected to inform us about desired data and methods for a more systematic approach to correlates and predictors of higher order thinking skills in institutions of higher learning.

Based on the results of this study, faculty who wish to increase the level of student motivation and higher order thinking skills in their classes should focus on improving the overall quality of their teaching, be sure to include elements of collaborative learning and teacher student relations, and to create a classroom environment that encourages relationships with other students. Such changes in teaching methods are likely to increase motivation and thus increased emphasis on higher order thinking skills.

Information about how students perceive the quality of teaching and learning, the effectiveness/enhancement of their own learning, and important elements of the learning environment can provide a rich base for enhancing the quality of teaching and learning in higher education settings.

Implications for Research Methodology

This study utilized a structural equation modeling technique which has tremendous advantages over traditional regression analyses such as: (a) SEM being a multivariate approach and structural/causal relationships are estimated at the level of latent variables or theoretical constructs rather than on the basis of the observed variables; (b) SEM procedures differentiate between a measurement model (describing relationships among observed variables and latent factors) and a structural model (describing interrelationships among theoretical constructs) thus allowing for a separate estimation of measurement errors in the observable specification of errors in the structural part of the model; and (c) SEM also provides an assessment of the degree of fit between the causal model and the data set to which it is applied (Koerkel & Schneider,1991; Kurtz-Costes & Schneider, 1994).

Further, the results of this study provide continuing support for the usefulness of the instrument used in the study as a measure of multiple dimensions of college/university teaching and learning environments.

APPENDIX A
FACTORS AND SAMPLE ITEMS OPERATIONALIZING EACH LATENT VARIABLE USED IN THE STUDY

Higher Order Thinking Skills (HOTS)

1. Developing concepts
2. Understanding and applying principles and rules
3. Understanding and applying theories
4. Critical analysis and/or problem solving

Self-efficacy (SE)

1. When there were difficult or uncertain obstacles to overcome in learning/achieving in this course, how much effort and persistence did you put forth to enhance your own learning?
2. How much knowledge and/or ability do you think you have to accomplish your learning objectives in college?
3. How much personal responsibility do you think you have to accomplish your learning objectives in college?
4. How much success do you think you have had in accomplish your learning goals in college?

Motivation (MO)

1. Encouragement for students to participate in discussions
2. The kind and number of thought-provoking questions asked
3. The extent to which students are encouraged to compare and contrast ideas
4. The extent to which students are involved in discussions among themselves
5. The degree to which students are encouraged to apply course content to solve problems or to understand real life situations

Teacher Students Relations (TSR)

1. The teacher considers my feelings
2. The teacher helps me when I have trouble with the work
3. The teacher talks with me

4. The teacher moves about the class to talk with me
5. It is alright for me to tell the teacher that I do understand

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11. INFLUENCING GROUP DECISIONS BY GAINING RESPECT OF GROUP MEMBERS IN E-LEARNING AND BLENDED LEARNING ENVIRONMENTS: A PATH MODEL ANALYSIS

INTRODUCTION

Computer-mediated communication (CMC), consisting of highly interactive communication tools, including electronic mail, electronic bulletin boards, asynchronous multimedia notebooks, remote screen-sharing, and desktop video teleconferencing, is becoming increasingly common in modern classrooms, in addition to face-to-face time between the instructor and the students. However it must be added here that the increase in the use of these CMC tools has been more to facilitate online learning for distance students, and in-class instruction still follows the traditional methods with a combination of face-to-face instruction and the use of CMC tools in student group projects. Synchronous interaction between remote participants in distributed learning environments has long been supported by audio and video teleconferencing via satellite and chat tools as well as the traditional telephone call. Developments in recent years have brought about the convergence of these channels of communication into a singular application interface allowing multipoint conferencing over the Internet – a virtual classroom. More recently texting has emerged as a medium of choice among students and the use of texting to facilitate knowledge transfer is currently being undertaken by several researchers.

Many university classes use Learning Management Systems (LMS) like Blackboard, BBLearn, and Moodle, etc., to post topics on the discussion boards, post grades and manage student projects. The use of these discussion boards allows students to discuss topics related to the material they are learning in class, allows them to interact with one another and the instructor asynchronously and also post, view and if required rate group projects. This allows for a certain level of peer involvement and assessment. Students' participation in discussion board threads allows for greater interaction in their instant messenger and email interactions, as they have had a chance to read and assess their classmates' contributions as they progress through the course. As predicted by Fishman (1995), such technologies have become more integrated into education, and, therefore, it is important to understand student learning, behaviors and attitudes towards the use of these communication technologies. The last couple of years have seen an increase in the

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 241–255.

use of social media sites like Facebook and Twitter for classroom activities, discussions and knowledge transfer. All in an effort to have the student/learner engaged and involved in the learning process as they interact with peers and instructors to achieve knowledge gains and other learning outcomes.

While Picciano (2002) raises questions regarding the nature and extent of these interactions and their effects on student performance, he reiterates that much of the research is based on student perceptions of the quality and quantity of their interactions and how much they have learned in an online course. In his study, Picciano (2002) examines performance in an online course in relationship to student interaction and sense of presence in the course and makes an attempt to go beyond typical institutional performance measures such as grades and withdrawal rates and to examine measures specifically related to course objectives. He found that though there was support for a strong relationship between students' perceptions and perceived learning, the relationship of actual measures of interaction and performance is mixed and inconsistent depending upon the measures and requires further study.

In our paper we present a hypotheses model about the communication medium in group discussions and that plays role in group members gaining respect from group members and influence in group decision making. The model further tracks the impact of how students motivated by the respect and influence, increase their participation in group interactions and the potential impact on their ability to make friends, collaborate and their perceptions of whether group members gained knowledge. We have analyzed the model using data collected over three time periods 2005-06 in a completely e-learning environment, in 2009-11 in a traditional classroom environment and in 2011-12 in a blended learning environment.

REVIEW OF LITERATURE

Many believe that online learning is the 'magic' answer to the pressure of growing enrolments, decreasing income, demands by students for more flexibility, along with the explosion in knowledge created in part by the communications revolution (Land, 2002; Race, 1998). The Internet brought with it opportunities for new communication media and tools and increasingly this has affected the way in which online and traditional courses have been developed, structured and delivered. Designers of online environments and CSCL systems have striven to make online learning more interactive through the use of tools for instructor-student and student-student interaction using both synchronous (instant messenger) and asynchronous (electronic discussion boards) communication. So the modern versions of the Learning Management Systems like BBLearn, Desire2Learn and others have tried to incorporate many features that facilitate these interactions.

CSCL was founded based on the idea that classrooms could be structured on the model of professional communities of practice that interactively and collaboratively built knowledge, such as scientific theories (Scardamalia & Bereiter, 1996). Following the principles of Vygotsky (1930/1978), knowledge was seen to be generally constructed socially in interactions among people before it was internalized as individual knowing. This social aspect was further developed into activity theory by Vygotsky's followers, emphasizing that individual cognition is mediated by physical and symbolic artifacts and that it centrally involves socio-cultural aspects. We extend that to include social dynamics factors of respect and influence in groups or communities. The socio-cultural aspects that arise as a result of social interactions among members of a group of students in a CSCL or blended learning environment form the basis of these social dynamics factors explained later on in the paper. An understanding of these factors will provide insight into the design of courses and systems to support collaborative learning and the development of respect, influence and teamwork in student teams.

Some researchers report that university students in online courses or in traditional face-to-face courses that include an online component appear to have found the online environment valuable for their learning (Ciba & Rakestraw, 1998; Morss & Fleming, 1998). Other researchers report that interactive online only courses allow for democratic participation (Schallert et al., 1999), and also that all class members have equal access to the floor (Bump, 1990; Hiltz, 1986). However, Hübscher-Younger & Narayanan (2003) have argued that power and authority have to be granted, and in the classroom the students hold the ability to grant authority, while the institutional status of an instructor gives some initial authority, students must consent and comply with the teacher's plans for her to have authority.

So democratization in the classroom and the shared power relationship need not always result in all participants getting equal access to the floor. Also, asynchronous discussions are not limited by 'real time', and allow each participant to contribute as much as she/he wishes to the group discussions. Again, Hübscher-Younger and Narayanan (2003), observe that despite the progressive teaching methodologies and CMC tools, the students still place authority with the teacher through valuing the teacher's opinions and approval and these student perceptions play a part in how the students view themselves and other members of their work groups for class projects, as well as how these groups perform and learn.

Yildiz and Chang (2003) found that the quality of feedback from peers and instructor in web-based courses was superior to that of face-to-face courses and onsite instructors should consider incorporating web-based asynchronous discussion to their face-to-face classroom. They recommend that researchers should examine how the quantity, quality or immediacy of feedback or response from peers or the instructor in web-based courses might differ in relation to these components (participation, grades, technology and course content) and to what extent they differ. Powers and Mitchell (1997) showed that a true community of learners can be developed in a web-based course despite the differences in their patterns of communication and interaction. They found that as regards to students' perceptions and performance, peer support, student-to-student interaction, faculty-student interaction and time demands were important themes and the unique nature of the technology and relative anonymity was perceived as one possible reason for community building.

While contemplating the physical separation of the learner and the instructor, Moore (1993), believed that this separation contributes to "psychological and communication gap" and he proposed and the developed "the theory of transactional distance", emphasizing the effect of distance on teaching as well as learning behaviors, forms of interaction, communication, instruction, and curriculum. He identified three components of distance education: dialogue, structure, and autonomy, where dialogue refers to the interaction via actions, words, or ideas between the instructor and learner or among learners. The nature and extent of dialogue depends on the course design, subject matter, medium of communication, personalities of instructor, learning styles of learners, and size of the class. Moore speculated that when everything else is controlled, chances are interaction between instructor and learners in a small class will be more frequent than in a large class (Moore & Kearsley, 1996). Moore (1993) further proposed that when similar media are used, graduate courses in social sciences and education tend to be more interactive with project work than those in sciences and mathematics that demand teacher direction.

Moore suggested that structure is determined by the educational philosophy of instructor, academic level of the learners, course content, as well as communication media (Moore & Kearsley, 1996). While autonomy on the other hand, is the extent to which learners have control over learning objectives, implementation procedures, resource, and evaluation (Moore, 1990, p. 13), with the belief that learners are capable of making decisions for their learning. Moore hypothesized the tendency that "the greater the structure and the lower the dialogue in a program the more autonomy the learner has to exercise" (Moore, 1993, p. 27).

In the case of blended learning environments, where students are co-located and groups are formed either by self-selection or by instructor assignment, the autonomy rests within the group in the decisions they make towards any group project objectives. The structures within groups, regardless of whether they are in distance or co-located, mediated or non-mediated environments, are formed based on task allocation, group member experience or expertise and emergent network positions (Sundararajan, 2010) and any autonomy is often gained based purely on performance. In groups where members are new to one another, each has to earn their credibility and respect by dint of their performance on allocated tasks, their contribution towards the group project and their ownership of each other's learning.

We thus see that a CSCL or a blended learning environment would have to take into account interactions among many people, mediated by various artifacts, and cater to the learning objectives of individuals and groups that will interact in this environment. The CMC/CSCL environment will provide some of the early mediating artifacts. The technology will likely introduce physical constraints by being impersonal, slow, confusing and at times not working at all, yet requiring that students use them. So students must first learn how to use the tools provided in the learning environment, get comfortable with them and the accompanying artifacts and then begin the learning process. These constraints are equally applicable to the instructor.

The goals of the group (or students in the class) activity (performance, rewards), its constraints (materials, time), its medium (computer support, meetings), its division of labor (group selection, mix of skills) and its social practices (homework, native language) are given by the larger community beyond the group or class itself (Stahl, 2004). The individual, group and community all develop new skills and structures through the influence of one unit upon the other; none is fixed or independent of the others; learning takes place at each unit and between them (Stahl, 2004). So CSCL and blended learning environment communication can be thought of as a mediated discourse, involving the knowledge of the language, symbols, metaphors, and shared meaning. The language, usually the medium of instruction, will take the shape of the course the instructor has developed, while the symbols, in face-to-face and mediated interactions will revolve around socially constructed and accepted norms of cooperation, 'espirit de corps', standards of behavior (online and offline) and a common goal of learning the subject matter. And collaborative discourse is situated in the shared understanding of the group members, which in turn is historically, socially, culturally situated (Stahl, 2004).

Johnson, Johnson and Holubec (1998) have suggested that students in work groups or a class environment tend to assign themselves according to four types of skills: forming skills, functioning skills, formulating skills, and fermenting skills. The student with forming skills will be the one to monitor turn-taking in the group. The roles for the group member with functioning skills will be to record the discussion, encourage all to participate, clarify/paraphrase the group discussion, and work to seek a group consensus. Formulating skills require a student to generate discussion and to summarize the group's work. Finally, the student with the fermenting role works to ask for justification of the group's outcome and also helps to give a rationale for the group's activities. In network terms, these roles can be assigned to each actor (student) or they earn these roles based on their past record and performance in other group or class activities.

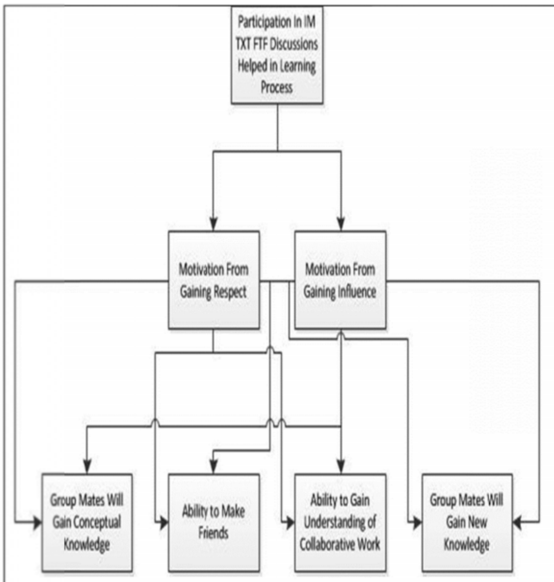
Cho, Stefanone and Gay (2002) in their paper, 'Social Network Analysis of Information Sharing Networks in a CSCL Community', clarify important features of social network analysis for analyzing community-based activities in a CSCL setting. They employed the theoretical and methodological background of social/communication network analysis to identify and understand students' communication and interaction patterns when collaborating through wireless computer networking tools. Their findings show that social influences, in the form of network prestige effects, strongly affected the likelihood and the extent to which information posted in the CSCL environment was shared by peers in this learning community. Thus participation in the group/class effort was validated by their peers and increased the network prestige efforts of the participants, motivating them to continue participating and collaborating.

It is difficult to assess the quality of learning in Computer-Supported Collaborative Learning (CSCL) or other blended learning environments, because standard pretest and posttest measures do not capture the differences in the learner's ability to engage in the material, pose interesting new questions, engage others in learning and work collaboratively. The above discussion makes the case for looking closely at social dynamics factors like respect and influence and other prestige effects as a useful set of factors to study students' interaction and participation in CSCL and blended learning environments and how they help the students in their learning processes and their possible impact on group learning outcomes. The aim of this research paper is to come up with stable measurements that can be replicated and serve as a guide to improved and more student-centered designs of mediated learning systems. We can now proceed to discuss the hypotheses model and explain in some detail the data collection procedures and the analyses that have been performed in this study.

RESEARCH HYPOTHESES

Respect and influence play a role in the formation of 'well-'oiled' group dynamics with communication and network factors leading to cohesion within the group and aiding in the formation of the above social factors leading to 'learning'. Lobel, Neubauer and Swedburg, (2005) explore how collaboration and interactivity are affected in the context of online learning by differences in what media allow in terms of turn taking. Haythornewaite (2005) states that research on computer-mediated collaborative practices show the interactions among the evolution of practice, the exchange of knowledge, and the use of computer media. As the guest editor of the Journal of Computer Mediated Communication's special theme issue on 'Computer-Mediated Collaborative Practices, Haythornewaite (2005) explains that each article in the issue, highlights the various facets of computer-mediated collaboration, i.e., the work of learning how to collaborate via computer media and evolve shared work and communication practices around and through information and communication technologies. She suggests that future work should extend and continue the evolution of computer-mediated collaborative practices, providing more cases on the interaction of people, practice and technology, extending the principles that underpin this kind of interaction, and demonstrating the impact of these practices through new approaches to measuring, collecting and communicating data on distributed practices. With this in mind, we propose the following sets of hypotheses. Figure 1 depicts the hypotheses in a schematic, while the adjacent column provides an explanation of the variables used in the model.

It is true that anyone can flood inboxes with emails, or the bulletin board with posts, or even make irrelevant remarks during an instant messenger conversation or send hundreds of text messages. However, only if the content of these emails, posts, text or chat responses are relevant to the topics under discussion, will they be received well. It is expected that everyone in the collaborative is reading the emails, message posts, chat or text exchanges, and being asynchronous in nature, these media allow participants to think about the content of the messages and respond in leisure. If the messages are more pertinent and helpful to the topics under discussion, the senders of these messages are viewed in a better light by the readers and will rise in the esteem of others in the collaborative environment. This then will motivate them to interact, participate, contribute and collaborate in



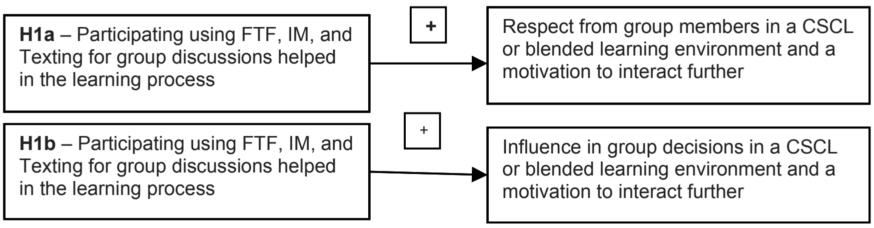
- One Communication Variable Assessing Role of FTF, IM and Texting for group interactions - **IMTXTFTF**
- Two Social Dynamics Variables: Motivation From Respect – **RESPMOTV** and Influence – **INFLMOTV**
- Two Collaboration Variables: Ability to make friends – **friends** and gain an understanding of collaborative and cooperative work – **collabwk**.
- Two learning outcome variables: Self-perception of group mates (distance or otherwise) gaining new knowledge – **grpnew** and Self-perception of group mates gaining conceptual knowledge – **grpcon**

Figure 1. Hypotheses Model

Explanation of Variables in the Model

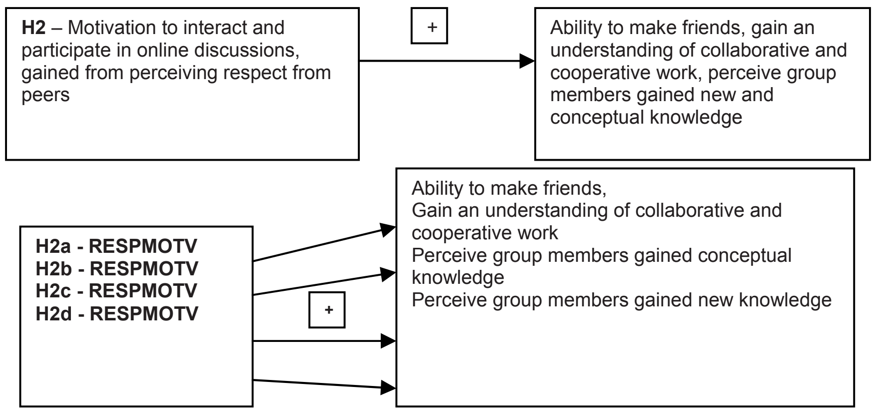
manner that benefits themselves and others in the class or group. Our first hypothesis, deals with the respect gained by peers while using technologically mediated communication tools/channels and the influence they gain in group decisions.

H1: Participating in class discussions using Face-to-Face (FTF), IM, or Texting will allow group members to gain respect from group members and give them influence in group decisions in CSCL or blended learning environments.

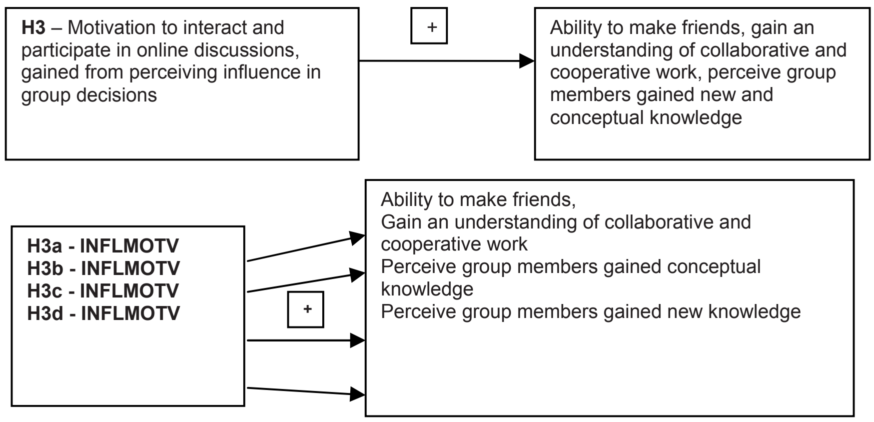


When group members gain respect of their peers in the group and also gain influence in group decisions, i.e. group members listen to and act upon proffered task/project related options, that will motivate students/group members to participate and interact more and increase their investment in the success of the group effort. This leads us to propose hypotheses H2 and H3.

H2: Motivation to interact and participate in mediated group discussions, gained from perceived respect from peers in a computer-supported collaborative learning (CSCL) or blended learning environment will positively impact the students' abilities to make friends, gain an understanding of collaborative and cooperative work, and perceive that group members gained new and conceptual knowledge.



H3: Motivation to interact and participate in mediated group discussions, gained perceiving influence in group decisions among students in a computer-supported collaborative learning (CSCL) or blended learning environment will positively impact the students' abilities to make friends, gain an understanding of collaborative and cooperative work, and perceive that group members gained new and conceptual knowledge.



METHODOLOGY – DATA COLLECTION AND SAMPLE

We present the results of analysis of data collected over three time periods. The first set of data was collected from eight courses over the period of three semesters, summer 2005, fall 2005 and spring 2006 at a university in the Northeastern USA. These courses were Global Marketing & Product Management (GMPM) in the summer of 2005, Foundations of HCI Usability (FHCI), Communication Design for the WWW (CDW) and Proposing and Persuading in the fall semester of 2005. Data from the following courses, IT and Decision Systems Capstone (ETC), Studio Design in HCI (SD), International Business (IB) and Theory and Research in Technical Communication (TCTR) was collected in the spring of 2006. However, despite repeated attempts to remind students to participate, very few actually did and we ended up with only 60 completed responses out of a possible 250 over all the courses. Out of the 60, we rejected 8 because they were duplicates and 3 more as the surveys were less than 60% complete. The final N was 49. Student groups consisted of 3-5 members. There was a mix of both distance students and in-class students all of whom used the Elluminate CSCL system.

The second data set was collected in two universities, one in Canada and one in the Southeastern US. The courses ranged from Business Communication to Strategy, Entrepreneurship and International Business. The initial N was expected to be over 250, however, we rejected several because they were either incomplete or had 5's or 3's or 1's as responses to the questions. The final N was 122. This data was part of an assessment study that involved group work and much of the group work involved face-to-face meetings and discussions, with email or texting only being used to set up meetings or exchange information or documents. Student groups consisted of 4-6 members. Students also had access to the Blackboard Learning Management System.

The third data set was part of a study in which we investigated the efficacy of texting and IM as a discussion medium in higher education classrooms. We conducted six rounds of testing in a special lab/classroom equipped with audio/video capabilities and also captured IM and text conversations. The courses taught were Tourism and Leisure Management and Corporate Communication and were conducted as compressed five-day courses. The final N was 77. Students were given a traditional lecture for an hour and twenty minutes and the lecture was followed by students discussing lecture related questions for about 30 minutes. They were then administered a survey on technology efficacy and learning outcomes. Students were divided into groups of 3-6. The study was conducted at a university in Canada. Student had access to material and collaborative tools in the campus LMS BBLearn.

All participants (across all three studies) answered several questions on a final end-of-study survey. While each of the studies had a different motivation, there were sixteen items that were common to all three studies. These sixteen items pertained to use of a communication medium (face-to-face, instant messenger, texting, email and electronic bulletin boards) for class discussions, social dynamics factors like respect from group members and influence in group decisions, motivation to participate in class discussions and individual and group learning outcomes regarding satisfaction with performance, gaining new and conceptual knowledge, making friends and learning about collaborative work. The learning outcomes related to both individual outcomes and group outcomes.

The focus of this paper has been the perceived group learning outcomes based on communication interactions and social dynamics factors. The Cronbach Alpha for these sixteen items was 0.886 (Hotelling's T-Squared F=16.719, $p < 0.001$). Of the sixteen items, we have used only seven in the hypotheses model (Figure 1) and the Cronbach Alpha for these seven items was 0.891 (Hotelling's T-Squared F=4.234, $p < 0.001$).

RESULTS

The way people participate and interact with each other provides information about the activities of the community. SEM is chosen to determine if the use or preference of a particular medium of communication (FTF, IM or Texting) supports the formation and sustenance of the social dynamics factors like respect, influence and teamwork, and have predictive capabilities in facilitating positive outcomes of group learning. Regarding sample size for SEM analysis, Bentler and Chou (1987) note that researchers can have as low as five cases per parameter estimate in SEM analyses, but only if the data are perfectly well-behaved (i.e., normally distributed, no missing data or outlying cases, etc.). In our case, the data, albeit collected over three different time periods, has been quite well-behaved. There is no missing data and any outliers have been removed (as discussed above). Further, running the individual datasets of (N=49, N=122 and N=77) resulted in roughly similar results, so combining all three datasets was not an issue. Further, the items' Cronbach Alpha has also remained quite steady across all three studies, indicating that the instrument was stable. The total N was thus 248.

Figure 2 represents the hypotheses model again, while Figure 3 represents the AMOS output model. For this model, the minimum was achieved with no errors and a Chi Square of 13.575 (df=4; p=0.009). While the Chi Square value, the absolute test of fit is low enough, the fact that the p value is not high causes us to pause and consider whether this model reflects a close enough fit. Table 1 shows the model fit summary.

Table 1. Model fit summary

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	31	13.575	4	.009	3.394
Saturated model	35	.000	0		
Independence model	14	994.997	21	.000	47.381

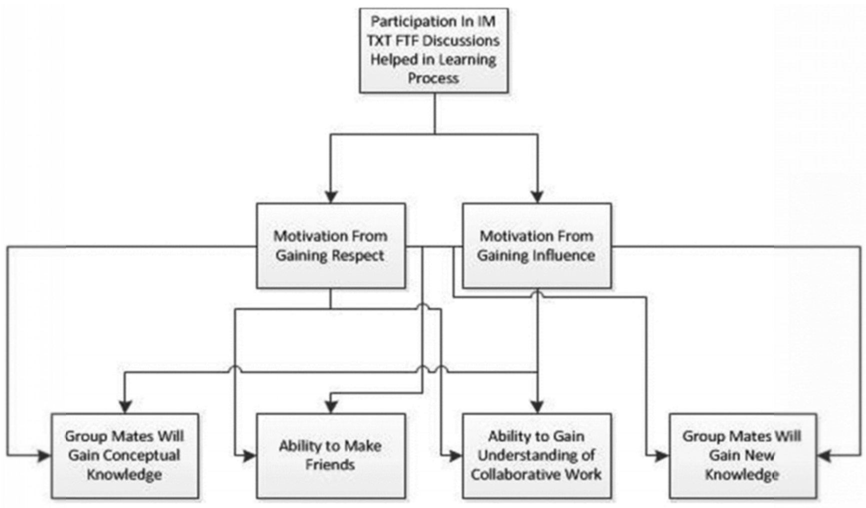


Figure 2. Hypotheses Model

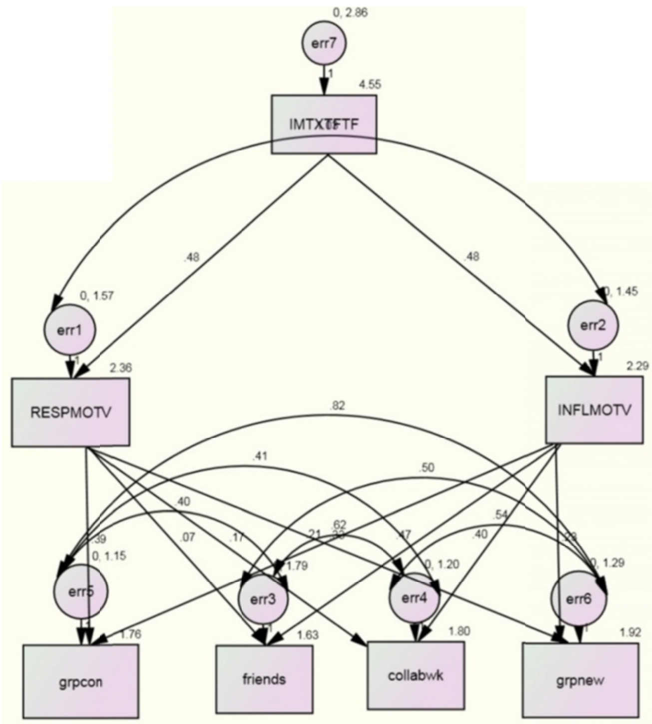


Figure 3. AMOS Output Model

Before reporting the regression weights of the individual relationships in the model, we report other model fit indices. The baseline comparisons of several fit indices resulted in the following values for NFI Delta1=0.986, RFI rho1=0.928, IFI Delta2=0.990, TLI rho2=0.948 and CFi=0.990. The RMSEA for this hypotheses model was 0.098 (PClose=0.067; LO 90=0.044; HI 90 = 0.158). All of this (including the commonly reported fit indices NFI, TLI and the CFI), indicates that the model has a relatively close fit, but there may be some elements in the model that prevent it from being a really close fit. We now discuss the regression weights between the variables.

Table 2. Regression weights for the hypotheses model

			Estimate	S.E.	C.R.	P	Label
RESPMOTV	<---	IMTXTFTF	.477	.047	10.122	***	par_4
INFLMOTV	<---	IMTXTFTF	.480	.045	10.603	***	par_5
grpcon	<---	RESPMOTV	.391	.073	5.358	***	par_6
grpnew	<---	RESPMOTV	.327	.077	4.232	***	par_7
grpcon	<---	INFLMOTV	.209	.075	2.792	.005	par_8
grpnew	<---	INFLMOTV	.226	.079	2.853	.004	par_9
friends	<---	RESPMOTV	.072	.091	.795	.427	par_14
collabwk	<---	RESPMOTV	.170	.075	2.282	.022	par_15
friends	<---	INFLMOTV	.469	.093	5.017	***	par_16
collabwk	<---	INFLMOTV	.404	.076	5.284	***	par_17

Looking at the regression weights for the hypotheses model listed in Table 2, we see that all but one of the relationships are significant at the $p < 0.05$ level (many at $P < 0.001$). We can summarize the significant relations below:

– Participants' perception that using FTF, IM or Texting for group discussions helped in their learning process is significant with participants perceiving that they gained respect from peers and motivated them to interact further in group discussions – IMTXTFTF $\rightarrow$ RESPMOTV (CR=10.122, $P < 0.001$) – **H1a supported**
– Participants' perception that using FTF, IM or Texting for group discussions helped in their learning process is significant with participants perceiving that they gained influence in group decisions and motivated them to interact further in group discussions – IMTXTFTF $\rightarrow$ INFLMOTV (CR=10.603, $P < 0.001$) – **H1b supported**
– Being motivated to participate by perceived respect from group members is significant with participants' perception that their group members gained conceptual knowledge – RESPMOTV $\rightarrow$ grpcon (CR=5.358, $P < 0.001$) – **H2c supported**

- Being motivated to participate by perceived respect from group members is significant with participants' perception that their group members gained new knowledge – RESPMOTV → grpnew (CR=4.232, P < 0.001) – **H2d supported**
- Being motivated to participate by perceived influence in group decisions is significant with participants' perception that their group members gained conceptual knowledge – INFLMOTV → grpcon (CR=2.792, P = 0.005) – **H3c supported**
- Being motivated to participate by perceived influence in group decisions is significant with participants' perception that their group members gained new knowledge – INFLMOTV → grpnew (CR=2.853, P = 0.004) – **H3d supported**
- Being motivated to participate by perceived respect from group members is significant with participants gaining an understanding of collaborative and cooperative work – RESPMOTV → collabwk (CR=2.282, P = 0.028) – **H2b supported**
- Being motivated to participate by perceived influence in group decisions is significant with participants ability to make friends – INFLMOTV → friends (CR=5.017, P = 0.005) – **H3a supported**
- Being motivated to participate by perceived influence in group decisions is significant with participants gaining an understanding of collaborative and cooperative work – INFLMOTV → collabwk (CR=5.284, P = 0.004) – **H3b supported**

We see that all the hypotheses, except H2a are supported. So while the results of the Chi-square test, CMIN value and RMSEA values indicate that the model fits the data acceptably, the individual parameter results are significant barring one relationship. The operationalizations of the concepts appear to be stable and they appear to be measuring what we set out to measure.

CONCLUSIONS, SUMMARY AND FUTURE DIRECTIONS

One of the goals of this study was to look at CMC-supported collaborative learning and blended learning and attempt to identify some of the underlying factors that improve the learning and collaboration. Respect as a social factor is important to people in order to validate themselves and the skills they bring to the table in collaborative work situations. Influence in a group and among class members and motivation to actively collaborate and not be a free rider, follow from the respect that the individual gets from group/class members. This respect may be there as a result of past achievements or may be earned by the individual during the course of collaboration. In either case, since respect and its companion, influence in a group, have emerged as important dimensions in collaboration among members in group/class project work, one can make a case for designing learning and collaborative systems which incorporate this need for validation.

Also, designing computer-mediated communication classrooms (CMCCs) in ways that promote more communication among group members through these methods is important, because student members that are typically shy or have language barriers avoid the communication methods most effective for building good social dynamics, even though there is a more urgent need for it. Such improvement in the class work environments can lead to better usage of the CMC tools, leading to better network structures among groups, better social interactions among group members and more successful outcomes in class efforts.

CSCL systems for supporting effective communication for building respect, influence and teamwork for collaborative learning could consider the following recommendations. They can have tools to validate the quality of the contribution to the work, for instance a tool that would prompt group/class members to send both a visual validation for work done, such as an emoticon, or textual feedback to their group members. This would be helpful in preventing situations in which members, who are contributing, don't feel valued and might feel like the payback for contributing in the work doesn't meet the cost.

A collaboration tool, especially if it is to be used by class/group members who do not have a history socially or in the workplace, should promote more 'intimate', spontaneous conversation. A lot of time is spent by groups in scheduling meetings and getting to know each other's schedule using email. Tools to support the sharing and setting of group calendars would help solve some of these problems and lead to an optimum level of group cohesion thereby facilitating collaboration and innovation. However, a lot of informal conversation surrounds the planning prior to collaboration that helps students get to know one another. They learn the other students' interests and responsibilities through just setting a meeting date and learning the others' day-to-day activities.

Tools to support group member learning outcomes where they can check of learning objectives and track each other's progress will also be a welcome addition to the CSCL or blended learning environments. Additionally, tools in these environments should also be inclusive, allowing people with all abilities and capabilities to participate and be heard. A rating meter to vote on suggestions, done anonymously, can also enhance group learning outcomes. Thus peer support becomes an integral part of the decision-making and the learning processes.

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12. INVESTIGATING FACTORIAL INVARIANCE OF TEACHER CLIMATE FACTORS ACROSS SCHOOL ORGANIZATIONAL LEVELS

INTRODUCTION

School climate and its importance to education and student learning have intrigued researchers for approximately 50 years (Anderson, 1982). A favorable school climate provides the structure within which students, teachers, administrators, and parents function cooperatively and constructively. Edmunds (1982) and Lezotte (1990) were prominent in linking climate directly to school effectiveness more than 20 years ago. School climate has been found to positively affect academic achievement (Greenberg, 2004; Lee & Burkham, 1996), and to influence a student's decision to remain in school (Byrk & Thum, 1989; Rumberger, 1995).

Hoy and Miskel (1982) defined school climate as a school's personality and every school may be thought of as having a distinct personality or climate. School climate is typically thought to involve four parts (Allen, Thompson, Hoadley, Engelking, & Drapeaux, 1997; Sackney, 1988): ecology, milieu, social system, and culture. Ecology comprises physical and material features of schools, such as age of the building and cleanliness. The milieu involves the personnel (e.g., administrators, teachers, parents, staff, students, etc.) involved with a school. A social system is described as the 'rules' which a school uses to interact with members. Finally, school culture consists of shared norms, values, and beliefs of the members. The two related topics of climate and culture are delineated by Allen et al. (1997) where, "culture establishes normative behavior for the members of organizations, and climate is the perceptions of those norms" (p. 1).

In the era of accountability, school climate is receiving increased attention. The importance of climate is highlighted when considering its effect on achievement and accountability measures. Specifically, a positive school climate has been found to correlate with higher rates of academic achievement including standardized test scores, as well as increased classroom engagement, student participation, and motivation to learn (CSEE, 2010; Chen & Weikart, 2008; DiStefano, Monrad, May, McGuiness, & Dickenson, 2007; Edmunds; 1982; Greenberg, 2004; Lee & Burkham, 1996; Lezotte, 1990; NSCC et al., 2008; Roney, Coleman, & Schlictin, 2007; Sebring, Allensworth, Bryk, Easton, & Luppescu, 2006; Stewart, 2008). Positive school climate has also been linked to indicators of school success reported for accountability purposes including annual yearly progress (AYP)

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measures and school report card information (Greenberg, 2004; MacNeil, Prater, & Busch, 2009; DiStefano et al., 2007; Monrad, May, DiStefano, Smith, Gay, Mîndrilă, Gareau, & Rawls, 2008; Tubbs & Garner, 2008). It is important to note that school climate is a malleable factor. In other words, compared with other barriers which cannot be controlled by schools (e.g., high family poverty), school climate is not a fixed school condition and can be changed (Greenberg, 2004).

When targeting school climate as an area for improvement, many factors come into play. Given the many stakeholders involved with education, perceptions of school climate may vary across different groups of people. While those interested in improving school climate may approach it from many angles, it seems likely to focus on teachers. Not only do teachers serve as the liaison between students, their parents, and school administrators, but also, workshops and programs aimed to improve school improvement are likely to be targeted to a schools' teaching faculty.

For school administrators and districts interested in working toward changing school climate, one additional factor to consider is the organizational level of a school. Typically, the perceptions of students and faculty in schools serving younger children (e.g., elementary) tend to be more positive than perceptions of students and teachers in schools serving older children (e.g., high school aged, DiStefano et al., 2007; Monrad et al., 2008).

While organizational-level differences relative to climate may exist, there may be elements of school climate that are similar for teachers of different developmental levels. For example, a study conducted by Johnston, Stevens and Zvoch (2007) tested the invariance of a teacher school climate structural model across organizational levels. The model tested consisted of five factors ('Instructional Innovation', 'Collaboration', 'Decision Making', 'School Resources', and 'Student Relations') each of which was subordinated to an overall second-order factor labeled 'School Climate'. Results showed that the estimated model worked equally well at the elementary, middle, and high school level. This study used data collected from teachers from a large urban school district located in the southeastern United States. Teachers completed a revised version of the School Level Environment Questionnaire, which included 21 items measuring perceptions of academic press, school leadership, school quality, and job satisfaction (Burden & Fraser, 1994; Fraser & Rentoul, 1982; Johnson & Stevens, 2001). The survey was completed by 2,558 of the teachers in one large school district, where roughly one-half of teachers (49.7%) worked in elementary schools (N=80 elementary schools) and the other half of the sample consisted of middle school teachers (25.9% teachers, N=26 middle schools) and high school teachers (24.3% teachers, N=13 high schools). While this study found similarities between teachers' perceptions of climate at different organizational levels, only one school district was used with a relatively small survey.

For over 20 years, South Carolina has been administering an annual school climate survey to all public school teachers across the state. Previous investigations using this survey have identified factors underlying the teacher climate surveys using exploratory factor analysis (DiStefano et al., 2007). This structure was replicated with confirmatory factor analysis and with five years of data (DiStefano et al., 2007; Monrad et al., 2008). While factors underlying the teacher survey have been identified and validated for the statewide survey, it is not known how teachers' views of climate differ based on the organizational level of the school.

The purpose of the current study was twofold. First, invariance testing was conducted to determine which aspects of school climate are similar across organizational levels. Additionally, latent means testing was used to identify potential differences of school climate by organization level to help inform school administrators. Second, the invariance testing conducted here used a very large factor model and large sample size. From a methodological perspective, this example provides information on statistics and indices under such situations.

METHODS

Teacher Survey of School Climate

Across the state of South Carolina, teachers at every school complete a survey each year to assess the learning environment, parent-school relationships, and social and physical factors related to each school. Three items from the survey are included on the school's report card, where only summary information noted (e.g., "I am satisfied with my school's learning environment"). However, many items are included on the survey and relationships among these items may represent underlying dimensions of school climate.

The survey is organized into four broad areas with nine items included in the *Learning Environment* area, 17 items for *Social and Physical Environment* scale, 11 items in *Home and School Relations*, and 14 items in the area of *Working Conditions*. Teachers respond to a set of 69 items using a 4-point Likert scale with anchors of: 1=Disagree; 2=Mostly Disagree; 3=Mostly Agree; 4=Agree.

Data

The data set used was collected state-wide at the end of the 2010-2011 academic year. Before analyses, duplicate cases were removed, as well as cases having more than 25% of the responses missing within each scale. For cases with 25% or less missing data on each section of the survey, missing item responses were imputed. Missing item data were replaced with the average of the individual's responses for other items on the same section, thereby maximizing sample sizes for analyses. The resulting data set provides a unique opportunity to examine the characteristics of school climate on a state-wide basis as well as conducting invariance testing with a large sample. Table 1 provides the number of teachers and schools included in the study by organizational level. For this study, nested relationships were not considered.

Table 1. Number of teachers and schools by organizational level.

	Organizational Level			
	Elementary	Middle	High	Total
Number of Schools	597	197	270	1,064
Number of Teachers	17,555	8,127	8,736	34,418

Prior Factor Analytic Work

The teacher school climate factor structure was derived from exploratory factor analysis (EFA) using the 2006 and 2007 teacher survey data. The 2006 sample was used to find an initial solution by reducing the pool of items through deletion of items that were cross-loading (above .4 on more than one factor) or had low loading values (under .2) with the associated factors. Additionally, items with low communality estimates (under .2) were deleted. This process resulted in a total of 15 items deleted from the scale, resulting in 54 items used for analyses. Multiple solutions were interpreted to identify an optimal number of factors underlying the data.

A six-factor solution was thought to fit the data: Working conditions/ leadership (WCL), Home-school relationship (HSR), Instructional focus (IF), Resources (RES), Social-physical environment (SPE), and Safety (SAF) (DiStefano et al, 2007). The survey items included in each factor are listed in the Appendix. The first factor, *Working Conditions/Leadership*, represented teachers' perceptions of the schools as a place of work and reflections on the administrative leadership. This factor included items such as: "The school administration provides effective instructional leadership" and "The school administration communicates clear instructional goals for the school." *Home-school Relationship* describes the relationship between parents and teachers and parent involvement with school activities (e.g., "Parents attend school meetings and other school events"). The third factor, *Instructional Focus,* measures an understanding of instructional standards and high expectations for students to meet those standards. The *Resources* factor reflects the materials needed to teach, including classroom space, textbooks, and computer capabilities. *Social-Physical Environment* measures teachers' views of the social-physical environment of the schools and were closely associated with building cleanliness and maintenance. The final factor, *Safety,* expresses teachers' perceived safety during the school day and while going to and coming from school. Some factors identified were similar in operational definition to those identified by Johnston et al. (2007) (i.e., School Resources). Remaining factors share similar elements with the work by Johnson and colleagues. For example, the WCL factor shares some of the same features included in the 'Collaboration' and 'Decision making' factors, and the IF factor includes some of the similar features to the 'Instructional Innovation' factor identified by Johnson and colleagues (2007).

The factor structure identified with the 2006 sample was independently replicated with data from the 2007 teacher survey. Again, the same six-factor solution was found optimal, with the same items selected for deletion. Because the factors did not change across the two-year period, this structure was used to specify a measurement model which included the six identified latent dimensions (Monrad et al., 2008). Confirmatory factor analysis (CFA) was conducted with school climate data for three subsequent years (academic years ending in 2008 through 2010). Results suggested that the items included in the measurement model were good indicators of the corresponding factors (Mîndrilă et al., 2010).

Invariance Testing of the CFA Model

The current study continued previous research by using the state-wide 2011 teacher survey data to investigate the invariance of the measurement model across school organizational levels, i.e., elementary, middle, and high schools. Multigroup invariance tests were conducted using the LISREL software program (version 8.80, Jöreskog & Sörbom, 1996). The Maximum Likelihood (ML) estimator was used as the fit function (Jöreskog & Sörbom, 1996). Although item data were ordinal, item level skewness values were under |2.5| across all three samples. Item level kurtosis values were under |4.0| for most of the 54 items examined, with the number of items exhibiting high kurtosis varying by level (4 items from the in high school sample, 10 from middle school, 20 in elementary school sample). While it is recognized that ML with non-normal data can produce attenuated loading values and biased fit indices (Finney & DiStefano, 2013), this estimator was used due to problems in computing a full asymptotic covariance matrix with such a large model.

With invariance testing, successive structural models, with more restrictions, are compared to models with fewer restrictions to determine if the imposed constraints impact the fit of the models. If there is no loss in fit, the models may be considered invariant, or equal, between groups. If model fit indices did not show a significant change between the less restrictive and the more restrictive model, the invariance testing continues with a new set of parameters. Otherwise, tests of partial invariance are conducted to identify which parameters within a group are responsible for the significant differences in model fit. The order of the invariance routine was based upon recommendations by covariance modeling researchers (Cheung & Rensvold, 2002; Finney & Davis, 2003; Vandenberg & Lance 2000).

The first step of the analysis was to test the configural invariance of the model across groups to determine whether the three groups associate the same subsets of items with the same climate constructs (Finney & Davis, 2003). At this stage, no equality constraints were imposed and all model parameters were left free for estimation (Model 1). Figure 1 depicts the baseline CFA model used in the analyses. The model includes unequal numbers of items per factor, with the largest number of items relating to *Working Conditions/Leadership* (14 items) and the smallest relating to *Safety* and *Physical Environment* (three items each).

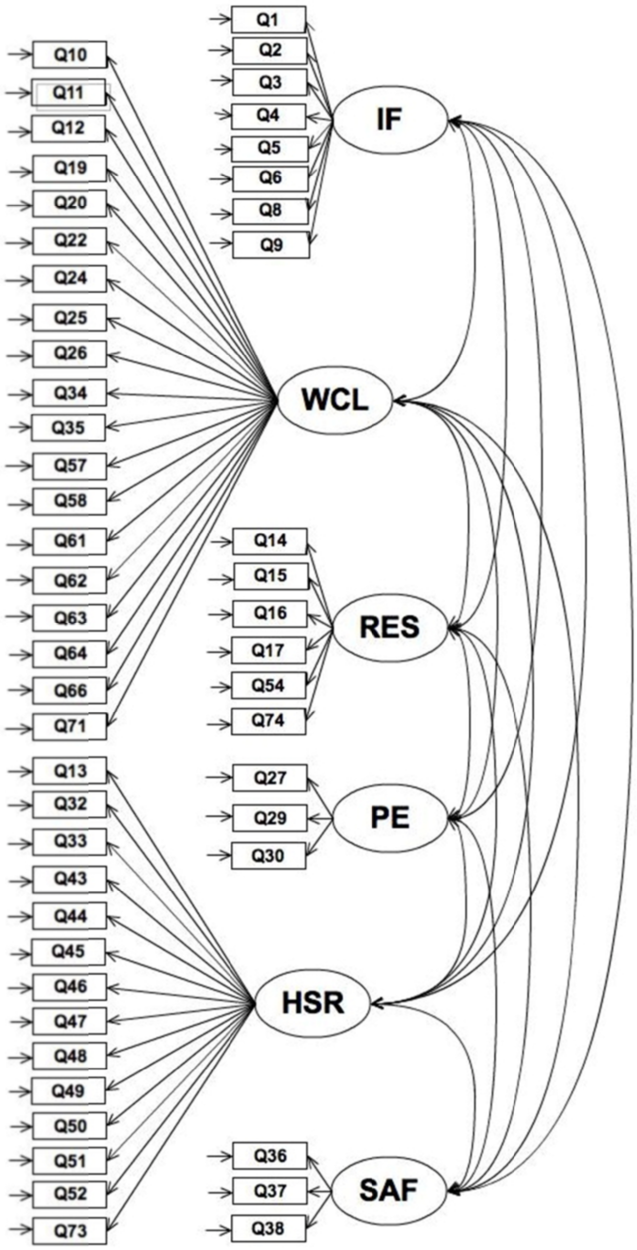

Figure 1. Baseline CFA model.
Note: IF= Instructional Focus, WCL = Working Conditions/Leadership, RES = Resources, HSR = Home/School Relations, PE = Physical Environment, SAF = Safety

The second step of invariance testing was to establish the metric invariance of the measurement model. The test of metric invariance is conducted by constraining all item loadings to be equal across groups (Model 2) and determining whether the model fits the data significantly better than Model 1. This procedure helps determine whether the relationships between items and the corresponding factors have similar strength across groups (Finney & Davis, 2003). If all loading values could not be constrained as equal, partial invariance was tested by allowing some loading values to be freely estimated within a group.

The next step was to hold factor variances equal across the three groups (Model 3). This procedure shows whether the range of factor scores on any of the school climate factors varies across groups (Finney & Davis, 2003). If Model 3 does not fit the data as well as the previous model, Model 2, the invariance testing procedures are stopped. Instead, researchers proceeded with tests of partial factor invariance, to identify the climate construct(s) for which the range of factor scores was statistically different across groups. This was done by sequentially holding subsets of climate factors equal across groups. If factor (partial) invariance was found, Model 4 constrained factor covariances to be equal. Again, all covariances were constrained equal initially and then partial invariance tests were conducted. This test determined if relationships among latent variables are similar across the groups.

Finally, the test of equal item error variances (i.e., uniqueness) is sometimes conducted. Many researchers consider this test to be rigorous (e.g., Byrne, 1998; Vanderberg & Lance, 2000); here, tests of equal item error terms were not of interest and were not conducted.

Latent Means Testing

It was of interest to test positions of the latent means on the variables to determine the perception of a given construct across organizational levels. Additional tests were included to investigate scalar invariance by adding restrictions from Model 2 plus the additional constraint of equal item intercepts, meaning that individuals with the same value on a given latent variable would report the same value on the observed variable, regardless of group membership (Hancock, 1997). If metric invariance and scalar invariance hold, tests for latent mean differences may be undertaken (Cheung & Rensvold, 2002; Vanderberg & Lance, 2000). Cohen's *d* effect size measure was computed to investigate the magnitude of the latent mean differences (Cohen, 1988) as compared to the elementary sample. The effect size was computed by dividing the latent mean difference by the pooled standard deviation (Hong, Malik, & Lee, 2003). While comparisons were conducted across two groups, the pooled standard deviation across the three groups was used to recognize the larger structure (cf. simple effects, Hinkle, Weirsma, & Jurs, 2002).

Evaluating Results

With invariance testing, fit indices used with CFA are used to assess the model fit at successive steps. Although the chi-square fit statistic is widely used as an index of how well the model fits a set of data, the index is sensitive to sample size and assumes the correct model is tested (Bollen, 1989; Jöreskog, 1993; Jöreskog & Sörbom, 1996). Therefore, models often will be rejected by a formal test of significance with a sufficiently large sample size (Marsh, 1996; Cudeck & Browne, 1983). Chi-square difference tests ($\Delta\chi^2$) may be calculated by comparing the difference in chi-square values between a more restrictive and less restrictive model to the referent value associated with the difference in degrees of freedom between the two models (Bollen, 1989). A problem when using such a large model and a large sample size is that the chi-square is sensitive to these conditions and also used in calculating many of the indices used to evaluate invariance.

The following indices were used in comparisons: NNFI, CFI, RMSEA, ECVI, and SRMR. Both the Non-Normed Fit Index (NNFI) and Comparative Fit Index (CFI) are incremental fit indices and test the proportionate improvement in fit between the tested model and a baseline model with no correlations among observed variables (Bentler, 1990; Bentler & Bonett, 1980). The values differ in that CFI is also adjusted for sample size. NNFI and CFI values approximating 0.95 were indicative of good fit (Hu & Bentler, 1999). Also, difference testing was investigated across models where ΔCFI values less than .01 may suggest invariance (Cheng & Rensvold, 1999).

The root mean square error of approximation (RMSEA) represents closeness of fit (Browne & Cudeck, 1993). The RMSEA value should approximate or be less than 0.05 to demonstrate close fit of the model, values between .05 and .08 represent reasonable fit, and values greater or equal to .10 suggest poor fit (Browne & Cudeck, 1993). The 90% confidence interval (CI) around the RMSEA point estimate should contain 0.05 to indicate the possibility of close fit (Browne & Cudeck, 1993).

The Expected Cross-Validation Index (ECVI) (Browne & Cudeck, 1993) is a single sample estimate of how well the current solution would fit in an independently drawn sample (Browne & Cudeck, 1993), and it can be used to compare the fit of competing models (Browne & Cudeck, 1993). SRMR is the standardized average absolute value of the covariance residuals between the specified and obtained variance-covariance matrices. Researchers typically use .08 as a threshold for good fit (Tanaka, 1993). The Expected Cross-Validation Index (ECVI) (Browne & Cudeck, 1993) is a single sample estimate of how well the current solution would fit in an independently drawn sample (Browne & Cudeck, 1993), and it can be used to compare the fit of competing models (Browne & Cudeck, 1993). ECVI also includes a 90% confidence interval which can be used when comparing models.

As a second check on model fit indices, invariance testing was run with five random samples ranging from of 1,000 to 20,000 cases with the "final" model. Here, sample size ratios approximating levels with the full sample (i.e., twice as many elementary responses). The purpose of these analyses was to not only determine if the same recommendations would hold with a smaller samples size, but to determine how fit indices may vary due to ratios related to the number of variables and parameters estimated.

RESULTS

Invariance Testing

We examined the fit of the models in the invariance routine by organizational level. Table 2 reports the fit information for the tested models. We first examined the fit of the base model (i.e., CFA model) within each of the three organizational levels separately. The base model represented acceptable model-data fit within each of the three samples. Although the chi-square statistics were significant, all fit indices exceeded recommended criteria and suggested good model-data fit.

Table 2. Invariance testing with full sample

	Configural	*Center*		*Scalar*	*Factorial*	
	Model 1 Free Form	Model 2 All Loadings	Model 2a* Partial Loading Invariance	Model 2b* Item Intercepts	Model 3 All Factor Variances	Model 3a Partial Invariance
Fit Indices						
Chi-square	208,050	212,049	211,410	219,538	213,625	212,665
df	4,086	4,182	4,174	4,270	4,186	4,178
RMSEA	0.0747	0.0748	0.0746	0.0754	0.0742	0.0749
ECVI	7.7477	7.9132	7.8766	8.2422	7.9696	7.9390
NNFI	0.9646	0.9646	0.9652	0.9721	0.9724	0.9724
CFI	0.9663	0.9656	0.9657	0.9723	0.9730	0.9732
Δ CFI	---	0.0007	0.0006	0.0067	0.0083	0.0082
SRMR	0.0550	0.0700	0.0680	0.0667	0.1379	0.1160

Note: * = Model 2b used for Latent Means testing.

We then compared the fit of the models in the invariance routine. There was evidence for the invariance of the overall structure (i.e., configural invariance – Model 1), where fit indices exceeded cutoff values. With Model 2, most indices were beyond stated cutoff values; however, given the increase in ECVI, we investigated individual items for partial invariance. Four items (Q5, Q8, Q44, and Q74) with loading values greater than .10 across factors (standardized solution) were allowed to be freely estimated in each sample. Allowing these items to be freed produced better fit, as shown by the reduction in ECVI and RMSEA. Therefore, we allowed for partial metric invariance.

Model 3 tested the factorial invariance of the latent variables. While invariance of factor variances met the criteria for invariance and good fit by some of the fit indices (e.g., ΔCFI , NNFI), the large increase in SRMR was disconcerting. Select variances were allowed freed across organizational levels in Model 3b. This model yielded better fit and a reduction in ECVI and SRMR; however, we stopped invariance testing at this point due to the high SRMR value.

Latent Means

Model 2b tested scalar invariance. Although there was support for scalar invariance from other fit indices, the ECVI increased; additionally, it was thought that the mean levels of individual items would be best to vary across levels to reflect differences in perceptions.

Therefore, scalar invariance was thought to be tentative and was used to investigate latent mean differences. To investigate latent mean differences between organizational levels, the latent mean values of the six climate constructs were fixed to zero in the elementary level group and freely estimated for middle and high school levels. Table 3 provides a summary of latent mean values. As shown in the table, estimated latent mean values for all factor means at middle school and high school level reported significantly lower perceptions of school climate than elementary level teachers. All values were statistically significant.

Table 3. Estimated latent mean values differences from elementary level

Level	*Working Conditions/ Leadership*	*Home/ School Relations*	*Instructional Focus*	*Resources*	*Physical Environment*	*Safety*
Middle	-0.207	-0.273	-0.085	-0.170	-0.044	-0.067
Effect Size	-0.288	-0.406	-0.224	-0.275	-0.095	-0.157
High School	-0.308	-0.437	-0.202	-0.305	-0.133	- 0.143
Effect size	-0.428	-0.651	-0.529	-0.493	-0.291	-0.332

Note: All latent mean values are statistically significant (p<.001).

Because significance may be partly due to the large sample size, Cohen's *d* effect size measures (Cohen, 1988) were computed to investigate the magnitude of the latent mean differences between elementary school and middle or high school, respectively. The computed values of *d* are provided in Table 3 and, as shown, differences by organizational level were observed. Considering Cohen's guidelines for interpreting effect size values, effect size values latent mean differences between elementary and middle school may be considered small to moderate. However, differences between elementary and high school teachers were mostly moderate. *Home-school relations* showed the largest differences between elementary and higher organizational levels; and *Physical Environment* showed the smallest difference among the groups.

Performance of Fit Indices Relative to Sample Size

Table 4 provides the sample sizes used in the analyses as well as the minimum sample size to number of variables ratio and the ratio sample size to number of parameters using Model 3a (partial invariance of factor variances) used as the final model.

Table 4. Sample sizes and ratios

	Elementary N	*Ratio N: var*	*Ratio N: param*	*Middle/ High N*	*Ratio N: var*	*Ratio N: param*
Sample Size						
1,000	500	9.3: 1	1.8: 1	250	4.6: 1	0.9: 1
2,000	1,000	18.5: 1	3.6: 1	500	9.3: 1	1.8: 1
5,000	2,500	46.3: 1	9.0: 1	1,250	23.1: 1	4.5: 1
10,000	5,000	92.6: 1	18.1: 1	2,500	46.3: 1	9.0: 1
20,000	10,000	185.2: 1	36.1: 1	5,000	92.6: 1	18.1: 1
Full Total	17,555	325.1: 1	63.4: 1	8,127/ 8,736	150.5/ 161.8: 1	29.3/ 31.5: 1

Note: Number of variables included = 54, Number of parameters estimated= 277.

Table 5 reports the fit indices by sample size. In terms of decision making, results are similar across the samples. RMSEA, CFI, and NNFI largely met the criteria for good fit across all the samples. NNFI and CFI were relatively constant across the samples drawn, suggesting that these indices may be useful under very large sample sizes. As expected, indices which rely on "smaller" values as indicative of "better" fit (e.g., RMSEA, ECVI, and SRMR) were lower (i.e., showing "better" fit) as sample size increased. SRMR reported higher levels of error for the lowest sample size; values were roughly stable above this sample size. RMSEA values were also similar across the set of random samples; however,

Table 5. Fit indices for random samples

	Sample Sizes					
	1,000	*2,000*	*5,000*	*10,000*	*20,000*	*34,118*
Fit Indices						
Chi-square	12,927	19,056	36,095	66,539	125,730	212,665
Df	4,178	4,178	4,178	4,178	4,178	4,178
RMSEA	0.0851	0.0807	0.0758	0.0759	0.0720	0.0749
90% CI	0.08357-0.08664	0.07970-0.08178	0.07513-0.07641	0.07551-0.07640	–	–
ECVI	14.8333	11.4483	8.9431	8.5074	8.1113	7.9390
90% CI	14.470-15.2007	11.2155-11.6844	8.8085-9.0788	8.4129-8.6022	–	–
NNFI	0.9558	0.9678	0.9700	0.9700	0.9720	0.9724
CFI	0.9570	0.9686	0.9708	0.9719	0.9727	0.9732
SRMR	0.1678	0.1141	0.1205	0.1247	0.1139	0.1160

Note: Confidence intervals could not be computed for largest sample sizes.

confidence intervals across samples did not overlap for most sample sizes, suggesting differences among results. ECVI reported the greatest fluctuation, with lower values as sample size increased and results yielding non-overlapping confidence intervals across samples.

DISCUSSION

The purpose of this study was to investigate teacher perceptions of school climate to determine which aspects were similar across organizational levels. Invariance testing was used with a state-wide teacher climate survey to determine how perceptions of climate varied between elementary, middle, and high school teachers. Six school climate dimensions perceived by teachers: Working conditions/leadership (WCL), Home-school relationship (HSR), Instructional focus (IF), Resources (RES), Social-physical environment (SPE), and Safety (SAF) were tested in a large model (54 items) with a sample size of over 30,000 teachers. Results supported configural and partial metric invariance. Four items were allowed to vary due to loading differences of .10 or higher across factors. These items largely measured school-based resources (e.g., school offers programs for students with disabilities, class size manageable, class time sufficient for learning essential skills) and may differ due to the characteristics of individual schools. The remaining item assessed parent knowledge of school activities; where it is well known that parent involvement decreases as the age of the child increases (Zill & Nord, 1994). This latent variable also showed the greatest differences in latent mean values for high school and middle school teachers as compared to elementary teachers.

The final model also suggested that the factor variances were largely different among organizational levels. Partial invariance was found where only two of the six factors, *Instructional Focus* and *Social/Physical Environment*, were similar across the groups. The IF factor measured teachers' knowledge of instructional standards and teachers across organizational levels stated similar views as to awareness of the material to be taught and of student expectations to meet state standards. Additionally, regardless of organizational level, teachers had similar perceptions about the physical environment of the school. Clean, well-maintained buildings and school grounds were equally important to teachers of all levels.

The amount of variability reported for the remaining four latent variables (WCL, HSR, RES, and SAF) was different across organizational levels. Generally, greater variability was seen for higher-grade levels taught. In other words, high school teachers' perceptions yielded greater amounts of variability than for middle school teachers. Elementary school teachers were the most homogeneous in their views of school climate. These variables also showed relatively low factor variances.

In general, the benefits of invariance across levels suggest that one structure can be used across organizational levels to summarize results. This is useful in that it allows school administrators to use a common model and perspective to discuss school climate for all organizational levels. This one structure can be used to obtain further information. Factor scores aggregated at the school level can be used to examine a school's perceptions of climate to determine school based strengths as well as areas for improvement. For example, cluster analyses were conducted using factor scores to identify different types of schools relative to climate and to differentiate groups using school report card information (DiStefano et al., 2007). Four climate clusters were uncovered where climate was described as Above Average, Average, Below Average or Well-Below Average. Schools with the most favorable school climates met more Adequate Yearly Progress (AYP) objectives, had higher standardized test scores, higher levels of parent participation, and more encouraging report cards. Generally, students performed at higher levels in schools with a positive climate, and students' performance was lowest in schools with the least favorable climate ratings.

Additionally, scalar invariance allowed for testing of latent means differences which may be used to identify differences concerning school climate. Not surprisingly, elementary teachers were significantly more positive than either middle or high school teachers relative to most school climate factors. However, this information can be used to help inform school administrators to improve school climate with respect to other schools at the same organizational level. The significant differences, as well as moderate effect sizes, found among latent means suggest that further analyses using mean scores should be 'split' by level to avoid confounding results. For example, correlational and regression analyses may be conducted for schools at a given organizational level to determine the relationship between school climate and selected accountability/school report card outcomes, (Monrad et al., 2008).

The information about fit indices under invariance testing with very large models and many items may be helpful to applied researchers. ECVI and SRMR showed the greatest fluctuations across the set of random samples, illustrating greater sensitivity to sample size with lower ratios of sample size to the number of parameters estimated or to the number of variables included. NNFI, CFI, and RMSEA were largely unaffected by varying sample sizes, showing acceptable fit across the set of tested models, even when ratios were very low. These indices should be examined further as prior work has found RMSEA to be overly optimistic when ordinal data are analyzed (DiStefano & Morgan, in press).

Limitations exist with the present study and with the dataset used in the analyses. Although the sample sizes were large, the analyses in this study were limited to data from a single school year, 2010-2011. Further, individual teachers cannot be identified in the dataset and all personnel within a school are required to complete the survey for report card purposes. Thus, not only are response rates not able to be reported, other personnel (e.g., school librarian, school counselor) may also take the teacher survey. While these personnel are affected by a school's climate, they may not relate to every indicator on the survey.

Additionally, districts vary widely in their capacity to support the schools' physical and learning environments. This variability may have an impact on school climate and, thus, survey responses. While the impact of district level indicators were not included in the present study, the role of district characteristics and support for improving school outcomes could be further explored through additional analyses, such as Hierarchical Linear Modeling.

Finally, this study used empirical data. While information regarding fit indices was examined using random samples of varying size, we cannot be sure that the true model was represented. Future simulation studies using large models and large samples will be helpful to see how fit indices perform under conditions where invariance is known.

There are also avenues for future research to improve school climate. The development of a school-climate report, designed expressly for school administrators and school improvement councils may be of interest. Such a report could be used to identify needed professional development and programmatic initiatives to improve school climate. Further, information could be used to reach out to parents for schools with lower climate ratings, thus showing parents the value of their input and hopefully encouraging higher levels of parent interaction. Future analyses may examine relationships between individual school climate factors and report card outcomes and provide schools instruction as to how to improve select aspects of climate.

This study allowed for a greater understanding of factors related to climate as well as information about how climate factors were similar and also different across school organizational levels. While one survey could be used to assess climate, differences do exist as to the level and variability of the latent variables among organizational levels. While many components of state accountability systems are beyond the power of a school to affect, school climate is unique in that it not only impacts achievement but it can also be changed, to provide a positive academic environment to foster learning.

APPENDIX

Items Used and Factors Constructed from the South Carolina Teacher School Climate Survey and Completely Standardized Loading Values

Factors and Items	Loading
Working Conditions and Leadership (19 items)	
Q10. The level of teacher staff morale is high at my school.	.75
Q11. Teachers respect each other at my school.	.56
Q12. Teachers at my school are recognized and appreciated for good work.	.79
Q19. The school administration communicates clear instructional goals for the school.	.80
Q20. The school administration sets high standards for students.	.75
Q22. The school administration provides effective instructional leadership.	.86
Q24. Teacher evaluation at my school focuses on instructional improvement.	.75
Q25. The school administration arranges for collaborative planning and decision making.	.70
Q26. I am satisfied with the learning environment in my school.	.82
Q34. Rules and consequences for behavior are clear to students.	.65
Q35. The rules for behavior are enforced at my school.	.70
Q57. I feel supported by administrators at my school.	.85
Q58. The faculty and staff at my school have a shared vision.	.81
Q61. The school leadership makes a sustained effort to address teacher concerns.	.87
Q62. My decisions in areas such as instruction and student progress are supported.	.81
Q63. Teachers at my school are encouraged to develop innovative solutions to problems.	.78
Q64. I feel comfortable raising issues and concerns that are important to me.	.81
Q66. I am satisfied with my current working conditions.	.80
Q71. School administrators visit classrooms to observe instruction.	.59
Home-School Relations (14 items)	
Q13. Students at my school are motivated and interested in learning.	.66
Q32. Students at my school behave well in class.	.67
Q33. Students at my school behave well in the hallways, in the lunchroom, and on school grounds.	.67
Q43. Parents at my school know about school policies.	.62

Q44. Parents at my school know about school activities.	.52 (.65, .74)
Q45. Parents at my school understand the school's instructional programs.	.72
Q46. Parents at my school are interested in their children's schoolwork.	.82
Q47. Parents at my school support instructional decisions regarding their children.	.81
Q48. Parents attend conferences requested by teachers at my school.	.78
Q49. Parents at my school cooperate regarding the discipline problems.	.80
Q50. Parents attend school meetings and other school events.	.81
Q51. Parents participate as volunteer helpers in the school or classroom.	.76
Q52. Parents are involved in school in school decisions through advisory committees.	.72
Q73. I am satisfied with home and school relations.	.84
Instructional Focus (8 items)	
Q1. My school provides challenging instructional programs for students.	.73
Q2. Teachers at my school effectively implement the State Curriculum Standards.	.76
Q3. Teachers at my school focus instruction on understanding, not just memorizing facts.	.78
Q4. Teachers at my school have high expectations for students' learning.	.77
Q5. There is a sufficient amount of classroom time allocated to instruction in essential skills.	.55 (.56, .52)
Q6. Student assessment information is effectively used by teachers to plan instruction.	.71
Q8. My school offers effective programs for students with disabilities.	.57 (.60, .51)
Q9. Instructional strategies are used to meet the needs of academically gifted students.	.64
Resources (7 items)	
Q14. There are sufficient materials and supplies available for classroom and instructional use.	.69
Q15. Our school has a good selection of library and media material.	.61
Q16. Our school has sufficient computers for instructional use.	.69
Q17. Computers are used effectively for instruction at my school.	.69
Q54. I have sufficient space in my classroom to meet the educational needs of my students.	.56
Q74. My class sizes allow me to meet the educational needs of my students.	.53 (.52, .50)
Physical Environment (3 items)	
Q27. The grounds around my school are kept clean.	.77
Q29. The bathrooms at my school are kept clean.	.79
Q30. The school building is maintained well and repaired when needed.	.83
Safety (3 items)	
Q36. I feel safe at my school before and after hours.	.90
Q37. I feel safe at my school during the school day.	.92
Q38. I feel safe going to or coming from my school.	.86

Note: Values in parenthesis are middle and high school values, respectively.

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INVESTIGATING FACTORIAL INVARIANCE OF TEACHER CLIMATE FACTORS

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PART IV

CONCLUSION

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13. STRUCTURAL EQUATION MODELING APPROACHES IN EDUCATIONAL RESEARCH AND PRACTICE

INTRODUCTION

Over the years, researchers have developed statistical methods to help them investigate and interpret issues of interest in many discipline areas. These methods range from descriptive to inferential to multivariate statistics. As the psychometrics measures in education become more complex, vigorous and robust methods were needed in order to represent research data efficiently. One such method is Structural Equation Modeling (SEM). With the advances in computational methods, statistical power to analyse complex data has been increased in recent years. Many educational researchers started using this technique in their research and the outcomes of the analysis help to identify the factors and interactions between students' characteristics, personal preferences, affective traits, motivational levels, study skills, engagement and various other factors that could help in educational practice (Teo & Khine, 2009). The chapters in this book presents the collective works on concepts, methodologies and ideas for SEM approach to educational research and practice. The anthology of current research described in this book will be a valuable resource for the next generation educational researchers.

The book is organized into three parts. Part I deals with theoretical foundations on the use of SEM in educational research. In Part II the research papers cover the use of SEM specifically in learning environment research and in Part III, Structural Equation Modeling in educational practice is presented followed by the conclusion.

THEORETICAL FOUNDATIONS

In Chapter 1, Teo from the University of Auckland and his colleagues from National Taichung University provided how Structural Equation Modeling (SEM) can be used as a method for analysing multivariate data both non-experimental and experimental in educational research. They noted that SEM procedures incorporate both unobserved (latent) and observed variables while other multivariate techniques are based on observed measurement only. They continue to identify types of models in SEM and explain in detail each of those models. It was also noted that there are five steps in testing SEM models. These five steps are model specification, identification, estimation, evaluation and modification. The

M.S. Khine (ed.), Application of Structural Equation Modeling in Educational Research and Practice, 279–283.

remaining chapter focused on the test of model fit and model modification. They concluded that the chapter presented non-technical, non-mathematical, and step-by-step introduction to SEM with a focus for educational researchers who possess little or no advanced Mathematical skills and knowledge.

Yo In'nami from Toyohashi University of Technology in Japan introduced the readers to Structural Equation Modeling (SEM) in a user-friendly way and lists some of the developments in the field of SEM applications. The chapter explained the principles, assumptions, strengths, limitations, and applications of SEM for experimental and non-experimental data. It describes five steps for SEM application: (a) model specification, (b) model identification, (c) parameter estimation, (d) model fit, and (e) model respecification. The chapter also provided brief insights into current issues in the field. Knowledge of these issues is vital for those who intend to use SEM. In addition, this chapter also described present and future trends with regard to the development of SEM to better prepare researchers for studying more advanced topics later in their careers.

STRUCTURAL EQUATION MODELING IN LEARNING ENVIRONMENT RESEARCH

Learning environment research, grounded in psychosocial contexts of the classrooms, has been firmly established as a field of study over the past four decades. Educators agree that, although important, academic achievement does not provide a complete picture of the process of education. The quality of the environment in which students learn plays an important role in achieving desired educational outcomes (Fraser, 2001). With the use of survey instruments and interviews with students, teachers and other stakeholders as a lens, educators are able to gain valuable information about the social ecology of the classrooms that could help to improve the instructional approach, classroom management and the learning organisation. Much research has been conducted to identify the factors and interactions between students' characteristics, personal preferences, affective traits, motivational levels, study skills, and various other factors that could help in organising conductive learning environments.

In recent years learning environment researchers used SEM as a tool to determine the effects of the classroom environments and psychological factors such as motivation, self-regulation, and attitudes towards subjects. Part II of this book contains six chapters that focus on the study of learning environments using SEM as an analytical tool. In Chapter 3 Marjan Vrijnsen-de Corte and her colleagues in the Netherlands presented the study on teachers' perceptions of the school as a learning environment for practice-based research. In their study, Structural Equation Modeling (SEM) was used to investigate paths (relations) between respondents' perceptions of the school as learning environment for practice-based research (research structure, research culture, and partnership), motives for performing practice-based research, process variables (planning and performing research, and evaluating and reporting research), and outcome variables (research attitude and efficacy beliefs, and teacher efficacy beliefs).

Chapter 4 by Liu and Fraser presented the development and validation of an English classroom learning environment inventory and its use in China and the associations between students' perceptions of the classroom learning environment and their English-related attitudes and academic achievement were investigated using structural equation modeling. The learning environment inventory measured the scales containing Teacher Support, Task Orientation, Student Cohesiveness, Cooperation and Oragnization. The inventory has 37 items. The attitude towards English was measured by Test if English-Related Attitudes questionnaire that has 8 items. The results from structural equation modeling are that Teacher Support, Task Orientation, Student Cohesiveness and Organisation had positive associations with students' English-related attitudes. The direct association between Task Orientation and attitudes was positive and statically significant, whereas Cooperation had a negative and significant impact on attitudes. The authors suggested that English teachers can make use the newly-developed inventory to assess students' perceptions for the improvements in their classroom environments.

Ennest Afari from the Petroleum Institute in Abu Dhabi presented his findings on the effects of psychosocial learning environment on students' attitudes towards mathematics in Chapter 5. This chapter reports a study that investigated the effects of psychosocial features of learning environment on college students' attitudes towards mathematics in the United Arab Emirates. The learning environment was assessed with two scales (Teacher Support and Involvement) from the What Is Happening In this Class? (WIHIC) questionnaire and one scale (Personal Relevance) from the Constructivist Learning Environment Survey (CLES). Structural equation modeling (SEM) was used to estimate and test the hypothesized relationships of 3 learning environment factors (teacher support, involvement and personal relevance) on enjoyment of mathematics lessons and academic self-efficacy. Results supported the positive effects of 2 learning environment factors (teacher support and personal relevance) on enjoyment of mathematics lessons and academic efficacy.

In Chapter 6, Valayutham, Aldridge and Afari described a comparative Structural Equation Modeling analysis on students' learning environment, motivation and self-regulation. The study aimed to identify salient psychosocial features of the classroom environment that influence students' motivation and self-regulation in science learning, and examine the effect of the motivational constructs of learning goal orientation, science task value and self-efficacy in science learning on students' self-regulation in science classrooms. Finally the study aimed to compare results from variance and covariance-based structural equation modeling (SEM) analysis. The comparative analysis of PLS and AMOS applications indicated that the results were similar for both confirmatory factor analysis and assessment of the research model.

The purpose of Hasan Seker's chapter (Chapter 7) is to show how SEM analysis can benefit learning environment research. His chapter dealt with in/out of school learning environment and SEM analyses of attitudes towards school. In Chapter 8, Lee her colleagues from Hong Kong presented a study that examined the effects of the teaching and learning environment on the development of students' generic capabilities. In their study the students completed a modified version of the Student Engagement Questionnaire, which measured their perceptions of the development of six capabilities and their ratings of the quality of six aspects of the teaching and learning environment. Structural Equation Modeling was used to test two alternative models on the impacts of the teaching and learning environment upon the development of the six generic capabilities based on samples of undergraduates.

STRUCTURAL EQUATION MODELING IN EDUCATIONAL PRACTICE

Part II of this book contains studies related to the use of SEM in educational practice. The section begins with Liem and Martin's work on the latent variabl modelling in educational psychology. The chapter described the many methodological applications of SEM that are used to answer distinct applied and substantive questions important to understanding and enhancing students' educational development. The chapter also synthesized findings from large-scale SEM studies conducted across elementary school, high school, and university/college. These studies encompass SEM involving, inter alia, longitudinal data, mediation, interactions, multi-group analyses, and multi-level modeling. The authors also presented some ideas for future SEM applications in educational research and practice.

In Chapter 10, John Rugutt from Illinois State University demonstrated the SEM approach to link teaching and learning environment variables to higher order thinking skills. Specifically the author of this study used the structural equation model (SEM) approach to test a model that hypothesized the influence of motivation (MO), teacher student relations (TSR), and self-efficacy (SE) on higher order thinking skills (HOTS). Also, the study used confirmatory factor analysis (CFA) to validate MO, TSR, SE and HOT measures. The study further investigated a SEM model that hypothesized interrelationships among all the study variables.

Binod Sundararajan and his colleagues from Dalhousie University, Halifax, Canada and North Carolina Central University, USA presented a path analysis model to examine the influence of group decision in e-Learning and blended learning environments. SEM was used to determine the effects of different variables such as motivation, respects, ability to make friends, self-perception of group mates and gaining new knowledge. Three hypotheses were tested and the data was analysed using AMOS. The authors concluded that both asynchronous and synchronous communication patterns in E-learning and blended learning environments allow learners to gain respect from group mates which then motivates them to have influence in group decision making processes, make friends, collaborate and have a significant impact on group knowledge gains.

In Chapter 12, Christine DiStefano and her co-researchers from the University of South Carolina and the University of West Georgia presented their finding from the factorial invariance investigation of teacher climate factors across school organizational levels. Six climate dimensions involved in this study were Working conditions/ leadership (WCL), Home-school relationship (HSR), Instructional focus (IF), Resources (RES), Social-physical environment (SPE), and Safety (SAF). Invariance testing and latent means comparisons were conducted by school organizational level to determine how the model structure, and resulting climate interpretations, may differ for teachers across elementary, middle, and high schools. The authors concluded that the results can be used to assist schools and administrators interested in enhancing school climate.

CONCLUSION

In sum, this book brings a range of international examples and theories to illustrate the applications of SEM in educational research and practice. The challenge for the researchers and educators is how we can make use of these results in practical ways for the improvement of future education and new generation of learners across the world.

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