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Influence of Teacher Support and Personal Relevance on Academic Self-Efficacy and Enjoyment of Mathematics Lessons: A Structural Equation Modeling Approach

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The purpose of our study was to examine the effects of two psychosocial features of the classroom environment (teacher support and personal relevance) on college students' academic self-efficacy and enjoyment of mathematics lessons. Data collected from 352 mathematics students attending three higher education institutions in the United Arab Emirates were used to validate the questionnaires and to investigate the hypothesized relationships. Structural equation modeling analysis suggests that teacher support and personal relevance are influential predictors of enjoyment of mathematics lessons and academic self-efficacy.

L'objectif de cette étude est d'examiner les effets de deux facteurs psychosociaux de la salle de classe (soutien des enseignants et pertinence personnelle) sur l'auto-efficacité académique des étudiants universitaires et du plaisir qu'ils retirent des cours de mathématiques. On a puisé dans des données recueillies chez 352 étudiants en mathématiques de trois institutions d'études supérieures aux Émirats arabes unis pour valider les questionnaires et vérifier les relations postulées. Une analyse de la modélisation par équation structurelle laisse supposer que le soutien des enseignants et la pertinence personnelle ont constitué des facteurs de prévision influents quant au plaisir que retirent les étudiants des cours de mathématiques et à leur auto-efficacité académique.

A substantial body of literature has consistently shown that learning environments influence students' academic self-efficacy, and that student self-efficacy beliefs regarding academic performance can have important implications for improving learning environments and student outcomes (Dorman, 2001; Dorman & Fraser, 2009; Lorsbach & Jinks, 1999; Velayutham & Aldridge, 2012). A study of classroom environment, perceptions of assessment tasks, academic self-efficacy, and attitudes to science revealed statistically significant links between classroom environment and academic efficacy (Dorman & Fraser, 2009). A more recent study (Velayutham & Aldridge, 2012) identified aspects of the psychosocial learning environment that influence student motivation (including self-efficacy). These results suggested that student cohesiveness, task orientation, and investigation are the most influential predictors of student self-efficacy.

Previous research has established that academic self-efficacy is a predictor of academic achievement (Bandura, 1997; Edman & Brazil, 2007; Gore, 2006; Hsieh, Sullivan, & Guerra, 2007; Tyler & Boelter, 2008) and that self-efficacy influences academic motivation and learning (Adeyemo, 2007; Pajares, 1996). Researchers have demonstrated that self-efficacy beliefs predict students' mathematics performance (Bandura, 1986; Pajares, 1996; Schunk, 1991). Interestingly, Pajares and Kranzler (1995) found that the influence of academic self-efficacy on mathematics performance was as strong as the influence of general mental ability. Hence our study aimed to investigate whether two psychosocial features of the classroom environment (teacher support and personal relevance) could influence students' enjoyment of mathematics lessons and academic self-efficacy in mathematics learning. Teacher support and personal relevance were selected because they have been shown to be strong predictors of student outcomes (Afari, Aldridge, Fraser, & Khine, 2013; Aldridge & Fraser, 2008; Veyalutham, Aldridge & Fraser, 2011). It was anticipated that this information could guide mathematics teachers. By focusing on the mathematics classroom environment, it might inform strategies for cultivating the levels of academic self-efficacy and enjoyment of mathematics lessons required to succeed in mathematics learning.

Our study was conducted in the United Arab Emirates (UAE), which is located at the southern tip of the Arabian Gulf and has a total area of 83,600 square kilometres. The country is bordered by Saudi Arabia, Qatar and the Sultanate of Oman. The UAE is a federation of seven independent states: Abu Dhabi, Dubai, Sharjah, Ajman, Umm al-Quwain, Ras al-Khaimah, and Fujairah.

It has been noted with concern that within the UAE educational system poor-quality instruction and learning exist in some college-level institutions and that, on the whole, teaching methods are based primarily on rote memorization (Gaad, Arif, & Scott, 2006; Shaw, Badri, & Hukul, 1995). Innovation by teachers is often viewed as difficult because of the demands of complying with a centralized curriculum and evaluation system overseen and enforced by administrators and school inspectors. Explanations and discussions are the most common teaching methods, with limited use of small group, individualized, experimental, laboratory, or role-playing methods. To overcome this, the Ministry of Education in the UAE adopted Education 2020, a series of five-year plans (up to the year 2020) designed to introduce advanced educational techniques, improve the innovative skills of teachers, and enhance the self-learning ability of students.

Research suggests that improving the classroom environment has the potential to improve student outcomes (Dorman & Fraser, 2009; Fraser, 2012). We undertook this study in the hope that establishing the influence of psychosocial aspects of the classroom environment (such as teacher support and personal relevance) on college students' academic self-efficacy and their enjoyment of mathematics lessons would have some implications for realizing the goals of Abu Dhabi's Education 2020. Since the field of learning environments emerged in the 1960s with the seminal work of Anderson and Walberg (1968) and Moos (1974), much progress has been made in conceptualizing and assessing learning environments. The field of learning environments has moved from a peripheral area in teaching and learning to being now recognized as addressing an important determinant of a range of student outcomes.

Learning Environment

There has been convincing evidence from studies conducted over the past 40 years that students learn better when they perceive their classroom environment as positive (Dorman & Fraser, 2009; Fraser, 2007, 2012). Numerous studies have shown that students' perceptions of the classroom environment account for appreciable amounts of variance in learning outcomes, often beyond that attributable to the students' background characteristics (Dorman & Fraser, 2009).

Recent studies have substantiated this position. For example, in California, USA, Ogbuehi and Fraser (2007) found associations between perceptions of classroom learning environment and students' enjoyment of mathematics among a sample of 661 middle-school students across 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) questionnaires. Kyriakides (2006) administered the Questionnaire on Teacher Interactions (QTI) (Wubbels & Levy, 1993) to a sample of 1721 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), and relationship between learning environments, family contexts, educational aspirations, and attainment (Marjoribanks, 2004).

Academic Self-Efficacy

More than three decades ago, Bandura (1977) theorized that a potent influence on students' 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, a major motivational component of expectancy-value theory is one's self-efficacy beliefs. In their expectancy-value theory, Eccles and Wigfield (2002) envisage a direct influence of students' expectation beliefs on both achievement-related choices and performance. According to Pajares (2002), self-efficacy is closely related to students' self-regulated learning. Students with high self-efficacy are increasingly likely to put in more effort, consistently evaluate their progress, and apply self-regulatory strategies (Schunk & Pajares, 2005).

Self-efficacy is one of the most consistently defined motivational constructs (Murphy & Alexander, 2001) and it refers to an individual's judgement about being able to perform a particular activity (Siegle & McCoach, 2007). Research over the past 35 years has revealed a positive relationship between self-efficacy beliefs and academic performance and persistence (Bandura, 1982, 1989; Martin & Marsh, 2006; Multon, Brown, & Lent, 1991; Skaalvik & Skaalvik, 2009; Zimmerman, Bandura, & Martinez-Pons, 1992). Previous research has established that self-efficacy is a predictor of academic achievement (Bandura, 1997; Edman & Brazil, 2007; Gore, 2006; Hsieh et al. 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 (Afari, Ward & Khine, 2012; Bandura, 1986; Pajares, 1996; Schunk, 1991).

In the UAE, Afari and colleagues (2012) investigated the relationships between global self-esteem, academic self-efficacy, and academic performance among 255 college mathematics students. Their results revealed that academic achievement was associated with having high academic self-efficacy. The purpose of our study was to investigate whether two psychosocial features of the classroom environment, teacher support and personal relevance, influence students' enjoyment of mathematics lessons and academic self-efficacy in mathematics learning in the UAE. This builds on and extends past studies that have found consistent links between students' enjoyment and self-efficacy and their perceptions of the learning environment (Fraser, 2012; Lorsbach & Jinks, 1999).

Learning Environments and Academic Self-Efficacy

Past research has reported strong and consistent relationships between academic self-efficacy and classroom learning environments in a range of countries. Research undertaken by Dorman (2001) indicated that the mathematics classroom environment is positively related to student academic self-efficacy. A study of classroom environment, perceptions of assessment tasks, academic self-efficacy, and attitudes to science revealed significant links between classroom environment and academic self-efficacy (Dorman & Fraser, 2009).

Previous research has shown that individuals with low self-efficacy tend to give up easily when faced with frustration, whereas self-efficacy and persistence increase with incremental successes (Lorsbach & Jinks, 1999). In China, Wu, Lowyck, Sercu, and Elen (2012) studied 78 second-year university students to clarify the interactions between task complexity and students' self-efficacy beliefs and students' use of learning strategies. Their study indicated a strong relationship between self-efficacy and learning outcomes, with learners with high self-efficacy beliefs having better task performances than learners with low self-efficacy beliefs.

Velayutham and Aldridge (2012) examined the influence of motivational constructs (learning goal orientation, science task value, and academic self-efficacy) in science learning on students' effort regulation in science classrooms. Their research involved 1360 science students in grades 8, 9 and 10 in Perth, Australia, and found that motivational beliefs of learning goal orientation, task value, and academic efficacy significantly influenced students' self-regulation in science learning.

Aldridge and Fraser (2008, 2011) explored associations between the classroom learning environment and student academic self-efficacy. Their research suggested that student academic self-efficacy was associated with the constructs of involvement, task orientation, investigation, cooperation, differentiation, computer usage, and young adult ethos. All statistically significant relationships were positive for both the simple correlation and multiple regression analyses, thereby suggesting a link between improved student academic efficacy and an emphasis on the dimensions of the classroom environment.

Results of past studies revealed positive relationships between students' enjoyment and self-efficacy and their perceptions of the learning environment (Ahmed, Minnaert, Werf, & Kuyper, 2010; Fraser, 2012; Lorsbach & Jinks 1999; Sakiz, Pape, & Hoy, 2012). Our study investigated two psychosocial features of the learning environments, teacher support and personal relevance, in mathematics classes and their relation to enjoyment of mathematics lessons and academic self-efficacy among college students in the UAE.

Research Model

We proposed a research model for our study, which is presented in Figure 1, based on the theory and the past research discussed above. The research model suggests that there are two latent variables: learning environment and attitude. The learning environment affects student responses to items relating to teacher support and personal relevance, while attitudes affect responses to questions relating to enjoyment of mathematics lessons and academic self-efficacy.

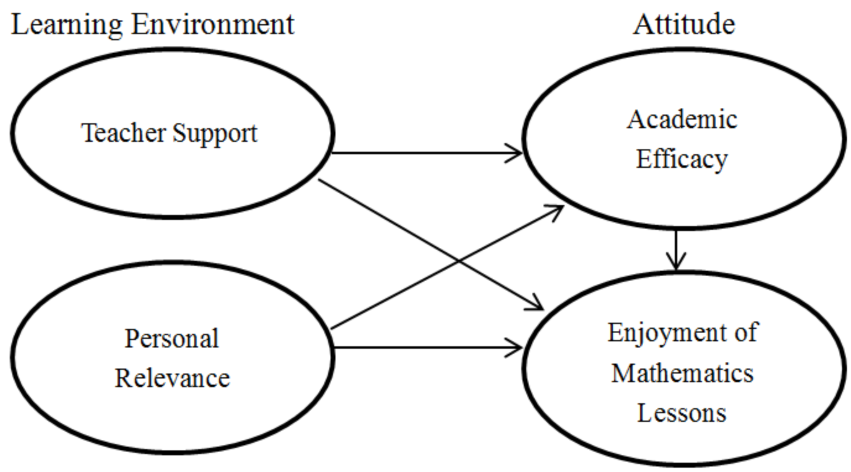

Figure 1. Hypothesised Structural Model for the Study.

The research model hypothesizes that each of the two psychosocial aspects of the learning environment (teacher support and personal relevance) influences each of the two attitude constructs (enjoyment of mathematics lessons and academic self-efficacy). Additionally, academic efficacy is predicted to influence enjoyment of mathematics lessons.

Methods

Participants

The sample for our study involved 33 classes containing a total of 352 students: 231 were female, and 121 male. Participants were drawn from three college-level public institutions located in Abu Dhabi, the capital and largest emirate (by area) of the UAE. The sample was randomly selected from the colleges in Abu Dhabi. All of the participants were in the foundation program of their respective universities and were preparing for careers in primary-school teaching, engineering, and business. The three institutions differed in terms of the mathematical abilities of their students. Most students attending the primary-school teaching college had majored in Arts in high school and were considered to have an intermediate level of mastery in mathematics. The participants in the engineering college, in turn, had majored in science during high school and were considered to have a strong background in mathematics. The participants in the business college were all mature-age students who had left school prior to completion and, therefore, were considered to have a low level of mastery in mathematics. Approximately 95% of the students were UAE nationals, while the remaining 5% of students were from other Arab nations. The students' ages ranged between 18 years and 35 years. Because all 352 students returned a fully completed questionnaire, there were no missing data.

Instruments

We adapted the Teacher Support scale, consisting of eight items, from the widely used WIHIC learning environment instrument (Aldridge, Fraser, & Huang, 1999; Fraser, 2012). 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. It can cause 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. In many ways, the teacher's relationship with his or her students is integral to a student's success and to creating a cooperative learning environment (Hijzen, Boekaerts, & Vedder, 2007; Wubbels, Brekelmans, van Tartwijk, & Admirals, 1999; Wubbels & Levy, 1993). Past research has shown that students' perceptions of teacher-student interpersonal behaviour are strongly related to student achievement and motivation in all subject areas (den Brok, Brekelmans, & Wubbels, 2004; Wubbels & Brekelmans, 1998) and that a healthy teacher-student interpersonal relationship is necessary for engaging students in learning activities (Brekelmans, Sleegers, & Fraser, 2000; Wubbels & Levy, 1993).

The response format for the Teacher Support scale involves a five-point frequency scale of Almost Always, Often, Sometimes, Seldom, and Almost Never. A typical item is "The teacher helps me when I have trouble with the work." The WIHIC has been found to be valid and useful in numerous past studies in several countries (Afari et al., 2013; Fraser, Aldridge, & Aldophe, 2010; Opolot-Okurut, 2010). In our study, the internal consistency (Cronbach's alpha) of the Teacher Support scale was .89 and considered to be satisfactory.

The Personal Relevance scale, consisting of eight items, was adapted from the Constructivist Learning Environment Survey (CLES) (Taylor, Fraser, & Fisher, 1997). To ensure that students engage in their learning, it is necessary for teachers to make the content of lessons 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 of Almost Always, Often, Sometimes, Seldom, and Almost Never. A typical item is "This class is relevant to my life outside college." The CLES was found to be valid and useful in numerous past studies in several countries (Aldridge, Fraser, Taylor, & Chen, 2000; Ogbuehi & Fraser, 2007; Peiro & Fraser, 2009). In our study, the internal consistency (Cronbach's alpha) of the Personal Relevance scale was .89 and considered to be satisfactory.

The eight-item academic self-efficacy scale was based on the Morgan-Jinks Student Efficacy Scale (MJSES) (Jinks & Morgan, 1999). 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 et al., 1992). The frequency 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." The Academic Self-Efficacy scale has been found to be valid and useful in numerous past studies in several countries (Afari et al., 2013; Aldridge & Fraser, 2008). In our study, the Cronbach alpha reliability for the Academic Self-Efficacy scale was .93 and considered to be satisfactory.

The Enjoyment of Science Lessons scale, modified for use in mathematics classes by Spinner and Fraser (2005), was used for our study. Spinner's and Fraser's (2005) version involves only items with a positive scoring direction and involved a rewording so that the word "science" was

Table 1

Scale Description and Sample Item for Each Questionnaire Scale

Scale Name	Scale Description	Sample Item
	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.
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.
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.

changed to "mathematics." For example, the item "Science lessons are fun" was changed to "Mathematics lessons are fun." The final version of this scale has eight items. In order to minimise confusion to students and be consistent with the response format of the WIHIC, the original format (Strongly Agree, Agree, Disagree, Strongly Disagree) was changed to a five-point frequency response format of Almost Always, Often, Sometimes, Seldom, and Almost Never and the wording of items changed accordingly. The Enjoyment of Science Lessons scale has been found to be valid and useful in numerous past studies in several countries (Afari et al., 2013; Aldridge & Fraser, 2008, 2011; Henderson, Fisher, & Fraser, 2000). In our study, the Cronbach alpha reliability for the Enjoyment of Mathematics Lessons scale was .95 and considered satisfactory. Table 1 provides a scale description and sample item for each of the scales used in our study.

Translation

The translation of learning environment questionnaires and the development of new instruments in languages other than English have provided useful tools for researchers in many parts of the world (Aldridge et al., 1999; Aldridge, Fraser, & Ntuli, 2009; Aldridge et al., 2000; Aldridge, Laugksch, Seopa, & Fraser, 2006; Fraser et al., 2010; MacLeod & Fraser, 2010). All of the questionnaires used in our study were originally developed in English. Even though the participants all spoke English as a second language, an Arabic translation still was created for those participants who were more comfortable with responding in their mother tongue. All of the items were translated into Arabic using the standard research methodology of translation, back translation, verification, and modification as recommended by Ercikan (1998) and Warwick and Osherson (1973). Each item was translated into Arabic by a professional translator and instructor from one of the colleges that the data were collected from. The next step involved an independent back translation of the Arabic version into English by another professional

Table 2

Descriptive Statistics for Teacher Support, Personal Relevance, Enjoyment of Mathematics Lessons, and Academic Self-Efficacy

Construct	Mean	Standard Deviation	Skewness	Kurtosis
Teacher Support	4.00	0.78	-.55	-.65
Personal Relevance	3.59	0.78	-.46	-.47
Enjoyment of Mathematics Lessons	3.60	0.99	-.73	-.24
Academic Efficacy	3.74	0.89	-.80	-.04

translator and instructor from the same college, who was not involved in the original translation, as recommended by Brislin (1970). Items in the original English version and the back-translated version were then compared to ensure that the Arabic version maintained the meanings and concepts of the original.

Descriptive Statistics

Some descriptive statistics for each of the constructs (Teacher Support, Personal Relevance, Enjoyment of Mathematics Lessons, and Academic Self-Efficacy) are shown in Table 2. All means were greater than 3.0, ranging from 3.59 to 4.00, indicating an overall positive response to the constructs that were measured in this study. The skewness ranged from -.46 to -.80 and kurtosis ranged from -.04 to -.65. Following Kline's (2010) recommendations that the skewness and kurtosis indices should be below an absolute value of 3.0 and 8.0, respectively, the data in this study were regarded as normally distributed for the purpose of structural equation modeling (SEM).

Convergent Validity

We used confirmatory factor analysis, involving SEM, to assess the measurement properties. The convergent validity and discriminant validity of the 32 items of the questionnaire were examined.

In assessing the convergent validity of the measurement items in relation to their constructs, item reliability of each measure, composite reliability of each construct, and the average variance extracted were examined, as proposed by Fornell and Larcker (1981). We checked the item reliability by assessing the loadings for each individual item (i.e. the correlation of the items with their respective constructs). As suggested by Nunnally and Bernstein (1994), maintaining items with low loadings would decrease the correlation between the items in the construct. Regarding reliability at the item level, the minimum requirement suggested for factor loading is .7 (Barclay, Higgins, & Thompson, 1995; Chin, 1998; Hair, Black, Babin, & Anderson, 2010; Hulland, 1999). Table 3 reports the item loadings, composite variance, and the average variance extracted for the research model. The results in Table 3 indicate that all factor loadings were above the recommended cut-off point. Thus, convergent validity was satisfactory at the item level.

Table 3

Item Loadings, Composite Variance, and Average Variance Extracted

Latent Variable	Item	Factor loading	Average Variance Extracted (AVE)	Composite Reliability (CR)
Teacher Support	TS8	.78	.59	.92
	TS7	.77		
	TS6	.83		
	TS5	.78		
	TS4	.73		
	TS3	.72		
	TS2	.75		
	TS1	.78		
Personal Relevance	PR8	.71	.57	.91
	PR7	.73		
	PR6	.79		
	PR5	.78		
	PR4	.79		
	PR3	.79		
	PR2	.74		
	PR1	.70		
Academic Efficacy	AE8	.74	.65	.94
	AE7	.70		
	AE6	.82		
	AE5	.79		
	AE4	.87		
	AE3	.81		
	AE2	.88		
	AE1	.81		
Enjoyment	EOM8	.88	.72	.95
	EOM7	.86		
	EOM6	.92		
	EOM5	.76		
	EOM4	.87		
	EOM3	.81		
	EOM2	.83		
	EOM1	.84		

Note: CR = $(\Sigma\lambda)^2 / (\Sigma\lambda)^2 + \Sigma(1 - \lambda^2)$; AVE = $\Sigma\lambda^2 / \Sigma\lambda^2 + \Sigma(1 - \lambda^2)$

At the construct level, an alpha reliability of .70 and higher is recommended to reflect adequate reliability (Nunnally & Bernstein, 1994). Table 3 shows that the reliabilities of all the constructs ranged from .91 to .95, which are above the minimum value recommended by Nunnally and Bernstein (1994).

The final criterion for convergent validity used was a measure of the average variance extracted (AVE) for each factor. Fornell and Larcker (1981) and Nunnally and Bernstein (1994) recommended a minimum value of .5 for AVE. Results of the analysis showed that the AVE values for all scales were above .5. Therefore, the measurement properties satisfied all three necessary criteria of convergent validity.

Table 4

Inter-Construct Correlations and Square Root of Average Variance Extracted

Construct	Teacher Support	Personal Relevance	Enjoyment of Mathematics Lessons	Academic Efficacy
Teacher Support	**.718**			
Personal Relevance	.185**	**.720**		
Enjoyment of Mathematics Lesson	.237**	.303**	**.835**	
Academic Efficacy	.117*	.208**	.479**	**.794**

Note: The bold elements in the main diagonal are the square roots of average variance extracted.
*$p < .05$; **$p < .01$

Discriminant Validity

Checking discriminant validity was the next step in the assessment of the measurement properties. Discriminant validity assesses the degree to which the constructs are empirically different. Table 4 reports the inter-construct correlations and square root of average variance extracted. The results (Table 4) support the discriminant validity because, for each construct, the square root of the AVE is larger than inter-construct correlation. The second discriminant validity criterion was that the loading of an item for a construct should be greater than its loading for any other construct in the model (Gefen, Straub, & Boudreau, 2000). Our results for cross-loading correlations (not reported here) confirmed that all items loaded more highly on the construct that they were measuring than on any other construct in the model. Therefore, the second criterion of discriminant validity was met. Overall, the two analyses supported that the individual constructs could be discriminated from each other.

Data analysis

We explored relationships among variables using SEM, with maximum likelihood estimation, using Analysis of Moment Structure (AMOS) version 18 software. SEM is a general term that has been described as a combination of exploratory factor analysis and multiple regression (Ullman, 2007).

SEM was chosen over the regression analysis that has been used frequently in this kind of study because SEM allows simultaneous analysis to be performed for assessing the relationships among variables and errors for each variable to be independently estimated, something that traditional regression technique cannot do. SEM allows the use of several indicator variables per construct simultaneously, which leads to more valid conclusions at the construct level than can be achieved using the traditional regression technique (Singh & Billingsley, 1998; Teo, 2009). Also, SEM can take measurement error into account by explicitly including measurement error variables that correspond to the measurement error portions of observed variables. Hence, conclusions about relationships between constructs are not biased by measurement error and are equivalent to relationships between variables of perfect reliability (Bollen, 1989, Kline, 2010). Another advantage of SEM is that it allows the modeling and testing of complex patterns of relationships, including a multitude of hypotheses, simultaneously (Bollen, 1989, Kline, 2010).

In this study, we first screened the data for missing responses and outliers. We then used confirmatory factor analysis to assess the measurement properties through an examination of convergent validity and discriminant validity.

Convergent validity assesses whether scores on items assessing a single construct are strongly intercorrelated and measure the same underlying dimension. Fornell and Larcker (1981) proposed three procedures for assessing the convergent validity of a set of measurement items, namely: item reliability for each measure; composite reliability for each construct; and the average variance extracted (AVE).

Regarding the item reliability of each measure, a factor loading greater or equal to .70 was recommended by Hair and colleagues (2010). At the composite reliability of each construct, an alpha coefficient of .70 or higher was recommended by Nunnally and Bernstein (1994) to reflect adequate reliability. The suggested minimum value of the average variance extracted (AVE) for each factor is .5 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994).

The discriminant validity, which is the extent to which a scale is unique in the dimension that it covers (i.e. the construct is not included in another scale of the instrument), was assessed by applying two analytic procedures suggested by Barclay and colleagues (1995). The first criterion of discriminant validity was that the square root of average variance extracted (AVE) for each construct be larger than the inter-construct correlation. As stipulated by Gefen and colleagues (2000), the second discriminant validity criterion is achieved when the loading of an item for a construct is greater than its loading for any other construct in the model.

The next stage of the analysis was the assessment of the research model using SEM. We used several fit indices to measure model fit as recommended by Harrington (2009) and Kline (2010). According to Brown (2006), fit indices are classified into the three categories of (1) absolute fit indices, (2) parsimony indices, and (3) comparative indices. Absolute fit indices measure how well the proposed model reproduces the observed data (Teo, Ursavas & Bahcekapili, 2012). The most common fit index is the model chi-square (χ^2). The standardized root mean square residual (SRMR) is another common absolute fit index. The next categories of fit indices are the parsimonious indices, which are similar to the absolute fit indices except that they take the model's complexity into account. An example is the root mean square error of approximation (RMSEA). Finally, the comparative fit indices are used to evaluate a model fit relative to an alternative baseline model (Harrington, 2009; Teo et al., 2012). Examples of comparative fit indices include the comparative fit index (CFI) and Tucker-Lewis index (TLI).

We finally tested the hypothesis outlined in the research model. The path coefficients, whether they were positive or negative, and the magnitudes of the hypothetical relationships were calculated. The purpose was to determine which constructs were significantly related in the research model.

Table 5

Fit Indices for the Research Model

Model Fit Indices	Values	Recommended Guidelines	References
χ^2	885.152 *P*< .001	Nonsignificant	Jöreskog & Sörbom (1993); Klem (2000); Kline (2010); McDonald & Ho (2002); Meeuwisse, Severiens, & Born (2010);
χ^2/df	1.967	< 3	Hu &Bentler (1999); Kline (2010);
TLI	.940	≥ .90	Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002);
CFI	.945	≥ .90	Bollen (1989); Byrne (2010); Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002);
RMSEA	.052	< .05	Browne & Cudeck (1993); McDonald & Ho (2002);
SRMR	.051	< .05	Hu & Bentler (1999); Klem (2000); McDonald & Ho (2002)

Results

Test of the Measurement Model

The research model in Figure 1 was tested using the SEM approach, using AMOS 18.0. In this study, all of the fit indices mentioned earlier were used. Table 5 summarises the commonly-used measures of model fit based on results from an analysis of the structural model, the recommended level of acceptable fit, and the fit indices for the research model in this study. All of the values satisfied the recommended level of acceptable fit with the exception of the χ^2. Hair and colleagues (2010) noted that, as the sample size increases, there is a tendency for the χ^2 to indicate significant differences. For this 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 5, indicate that the research model fits the data fairly well.

Testing of the Structure Model

The resulting path coefficients of the proposed model (Figure 1) are shown in Figure 2. Overall, four out of five hypotheses were supported by the data. Teacher Support did not have a statistically significant influence on academic efficacy (β = .120, p> .05), but had a statistically significant influence on Enjoyment of Mathematics Lessons (β = .173, p< .001). Personal Relevance had a statistically significant influence on Enjoyment of Mathematics Lessons (β = .171, p< .001) and Academic Efficacy (β = .245, p< .001). Finally, Academic Efficacy had a statistically significant influence on Enjoyment of Mathematics Lessons (β = .566, p< .001).

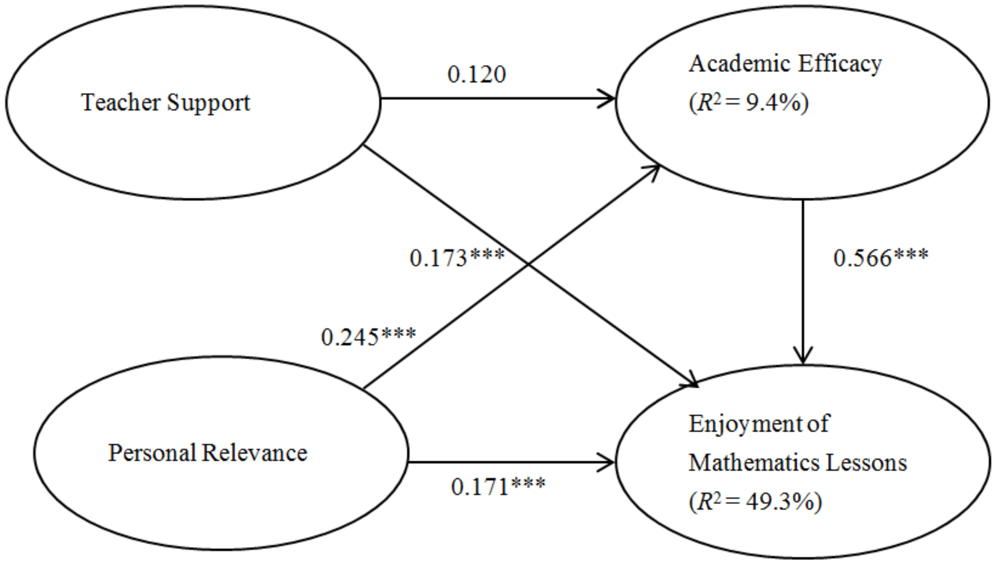

Figure 2. Standardised Path Coefficients.
***$p < .001$.

Two endogenous variables were tested in the research model. Academic Efficacy was found to be predicted by Teacher Support and Personal Relevance, resulting in an R^2 of .094. This means that Teacher Support and Personal Relevance explained 9.4% of the variance in Academic Efficacy. Also, Enjoyment of Mathematics Lessons was found to be predicted by Teacher Support, Personal Relevance, and Academic Efficacy, resulting in an R^2 of .493. This means that Teacher Support, Personal Relevance, and Academic Efficacy explained 49.3% of the variance in Enjoyment of Mathematics Lessons. The results of the hypotheses testing and path coefficients for the proposed model (Figure 1) are reported in Table 6.

Table 6

Hypothesis Testing Results

Path	Path coefficient	*t*	Results
Teacher Support → Enjoyment	.173	3.602***	Supported
Teacher Support → Academic Efficacy	.120	1.968	Not supported
Personal Relevance → Enjoyment	.171	3.467***	Supported
Personal relevance→ Academic Efficacy	.245	3.889***	Supported
Academic Efficacy→ Enjoyment	.566	10.203***	Supported

***$p < .001$

Table 7

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	.173***		.173***	.120		.120
Personal Relevance	.171***	.139***	.310***	.245***		.245***
Academic Efficacy	.566***		.566***			

Note. The sample consisted of 352 students in 33 classes in the United Arab Emirates.
***p<.001.

Path Analysis

We interpreted the structural relations in the model as the effect of one latent variable on the other. Table 7 shows the standardized total effects, direct effect, and indirect effects associated with each of the four constructs. As suggested by Cohen (1992) and Kline (2010), the effect sizes with values less than .1 were considered small, those less than .3 were considered medium, and values .5 or greater were considered large. All path coefficients were statistically significant with the exception of Teacher Support on Academic Efficacy. The largest effect in the model was for the influence of Academic Efficacy on Enjoyment of Mathematics Lessons (β = .566).

The two learning environment variables (Teacher Support and Personal Relevance) influenced both students' Enjoyment of Mathematics Lessons and their Academic Efficacy. Teacher Support had a medium direct effect (β = .173) 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 medium direct effect (β = .171) and also a medium indirect effect (β = .139), and so the total effect of Personal Relevance on Enjoyment of Mathematics Lessons was medium (β = .310). This effect suggests that, as students perceive more Personal Relevance, they enjoy their mathematics lessons more.

Finally, Personal Relevance had a medium direct effect (β = .245) on Academic Efficacy but no indirect effect. Hence the total effect was medium (β = .245). This suggests that students who have positive perceptions of Personal Relevance are likely to have moderately more positive Academic Efficacy.

Discussion

The main purpose of this study was to examine the influence of teacher support and personal relevance on students' academic efficacy and their enjoyment of mathematics lessons. The findings suggest that these two aspects of the learning environment, teacher support and personal relevance, had a statistically significant influence on students' enjoyment of mathematics lessons and academic efficacy. The relationship between academic efficacy and enjoyment of mathematics lessons was far stronger than any of the relationships involving teacher support and personal relevance.

The results suggest that students' enjoyment of mathematics lessons was more positive in classrooms with greater teacher support and personal relevance, and that academic 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, it is more likely that they will enjoy mathematics lessons. The results also indicated that increased academic efficacy was found with more personal relevance and enjoyment of mathematics lessons. Students' perceived personal relevance facilitated their academic efficacy which, in turn, enhanced their enjoyment of mathematics. The findings show that students who have perceived their personal relevance as positive also appeared to possess confidence in their academic competence. Such students in general enjoy mathematics lessons. Teachers should therefore be encouraged to nurture students' self-efficacy beliefs as these are related to academic success. Also, teachers might promote student enjoyment of mathematics by creating classroom environments that emphasise personal relevance and teacher support.

Consideration of the total effects revealed the important influences of teacher support and personal relevance on students' enjoyment of mathematics lessons and academic efficacy. Students' enjoyment of mathematics lessons was strongly affected by their perceptions of their academic efficacy, which is consistent with recent studies that have reported academic enjoyment to be significantly positively associated with students' academic efficacy (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011; Sakiz et al., 2012).

Results of our study indicated a statistically significant total effect for 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 mathematics lessons. Increased support by teachers might help students feel more comfortable in the classroom and this could lead to higher enjoyment of mathematics lessons. It is possible that feedback information provided through students' perceptions of the learning environment could help teachers in the UAE make changes to their mathematics classrooms. With more positive attitudes towards mathematics classes, it is possible that more students might choose to pursue mathematics-oriented courses in college and mathematics-related careers.

The generalization of the results to other populations should be made with caution because this study involved a relatively small number of students: 352 students in 33 classes from three colleges in Abu Dhabi. Although the UAE is a country with seven emirates (states) with at least five colleges in each emirate, no sample was drawn from any of the other six emirates. Also, all of the participants were in the foundation programs of their respective colleges. Therefore, caution is required when generalizing to other populations and settings. A further limitation of our study is its limited scope in terms of student outcomes, which included only students' academic efficacy and their enjoyment of mathematics lessons. In particular, the absence of any achievement outcomes might be considered as a limitation that should be overcome in future research. Other limitations are the multilevel nature of our study and also the fact that our analyzes were correlational in nature and hence no causal inferences among the variables are warranted.

The research reported in this article is significant because it is one of the few studies conducted in the UAE for which SEM has been used to develop a comprehensive model of the relationships among classroom environment and outcomes. Hopefully, the results of this study will encourage teachers—especially in the UAE—to improve their classroom environments, which is likely to lead to improved student outcomes. Also mathematics teachers could be encouraged to provide a learning environment with a cooperative atmosphere in which students feels that they are supported by their teachers and that mathematics lessons are made relevant to them. The results of our study have the potential to motivate educators and policy makers to improve learning environments by emphasizing cooperative work, active participation, and teacher support, which hopefully will lead to improved students' enjoyment of their lessons and confidence in their academic competence.

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