PSYCHOSOCIAL VARIABLES THAT AFFECT STUDENTS' EFFORT IN MATHEMATICS

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ABSTRACT: What does affect students' effort in mathematics? What is the relationship of variables such as math-level, anxiety, teacher support, self-concept and motivation with students' effort to learn mathematics? The relationships of the five variables with students' effort in mathematics are complex, which made us use a correlation cross-sectional design to study them. Doing so, we conducted a Structural Equation Modeling (SEM), using self-report measures of the various variables, to examine the relationships of the five variables with effort, for eighth, ninth and tenth grade students. We assumed that teacher support, which is a social variable, is one variable that needs to be an independent variable in the model. To account for the individual variable, we chose once student math-level and once student self-concept. Seven hundred and twenty eighth, ninth and tenth grade students completed the questionnaires. There were 381 males and 339 females. All participants were from northern West Bank in Palestine, at upper primary governmental schools. The research results show that there are two models that can explain the relationships between the variables and that could affect student effort to learn mathematics. The two models differ in the consideration of self-concept. One of them considers self-concept a dependent variable, while the other considers it an independent variable.

Keywords: Effort in mathematics, self-concept, math anxiety, teacher support, math level, motivation

INTRODUCTION

What does influence students' effort in mathematics? Some researchers attempted to find the influence of effort as an independent variable, finding that increasing one’s effort results in more ability (Resnick & Hall, 1998). This role of effort in increasing students' abilities in mathematics makes it necessary to try to influence it in several ways. Fiore (1999) says that reinforcing effort in math begins with helping students to develop positive self-concepts. To do so, Shinn et al. (2003) suggested different; one of which is teaching keeping in mind that students have understanding of mathematics, which lessens their anxiety (Reyes, 1980). So, anxiety is related to effort. The other methods are related to teacher role and support, as creating a comfortable class environment that emphasizes learning through participation, where students ask questions (Tobias & Weissbrod, 1980). These methods emphasize teacher role and support as a factor which affects student effort. These researches encouraged us to study the factors that affect student effort to engage in mathematical activities. We included teacher support, self-concept and anxiety, for they have been mentioned, as described before, as variables that affect student effort to do mathematics. As to motivation, some researchers connected effort to motivation, saying that the extent of effort affects student motivation to learn, as they could be unmotivated to learn if the effort needed to do so is so great (Wright, 2012). On the other hand, researchers pointed at motivation as a factor that could affect student effort (Usher & Kober, 2012). In more detail, Usher and Kober (2012) consider rewards (an external motivation component) a variable that encourages students to spend effort in their learning. In the present research, we examine how motivation can affect paths to effort.

The variables that affect student effort could be categorized as social and individual variables, or as environmental and personal variables, where the environmental variable is mostly represented by teacher support.

Teacher Support

Do teachers influence students' learning and classroom behavior, including effort? And if they indeed do, what kind of influence do they have on student learning? The question of how or whether teachers impact student learning has preoccupied educational researchers for a long time. This issue is especially important in light of Coleman Report (Coleman, 1990), released in 1966 (Coleman, 1990). The Coleman report used aggregated measures of school inputs in terms of facilities, teacher characteristics (average educational level of the teachers' families, average years of experience, on average whether teachers were local to the area, the teachers' average level of education, the teachers' average scores on a self-administered vocabulary test, the teachers' preference for teaching middle-class, white-collar students, the proportion of teachers in the school who were white), and student characteristics to study the effect of the school on students' achievement. The report showed that student characteristics, such as student socio-economic status [SES], parental educational attainment, poverty and student attitude towards schooling, influenced student achievement more than teachers and schools (e.g., Meyer, 1996; Porter & Smithson, 2000). Moreover, teachers become influential on student achievement when the previous variables are controlled for (e.g., Darling-Hammond, 2000; Haycock, 1998).

On the other hand, some researches found that teachers, when certain conditions are satisfied, contribute positively to students' learning. Wenglinsky (2001) mentions two conditions that ensure the improvement of student performance. First, the rigor of the academic standards and the alignment of curriculum and assessments to those standards, and, second that teachers possess the skills to teach according to the standards. Moreover, Rimm-Kaufman and Sandolis (2011) claim that improving students' relationships with teachers has positive influence on students' academic and social development. This is not done solely by improving students' relationships with teachers, but by ensuring that teachers provide close, positive and supportive assistance for their students.

The literature described above shows that the teacher's role in influencing achievement is disputed but his/her assistance in supporting learning is more acknowledged when the teacher provides appropriate support for students. This claim is affirmed by Usher and Pajares (2009) who say that the social persuasions that students receive from parents, teachers, and peers whom students trust serve as a source of self-efficacy. This is because the social persuasions can boost students' confidence in their academic capabilities. This is true particularly when accompanied by instruction that help the students reach their academic goals. Moreover, this is especially true when teachers work on teaching specific behaviors such as decoding tasks, perseverance, seeing difficulties as opportunities, and learning from mistakes (Dweck, 2000).

The previous claim of the teacher mediating role in motivating students to learn and thus affecting positively their effort is also supported by Russell (1999) and Fast et al. (2010). Russell (1999), as reported in Shinn et al. (2003), claims that teacher can provide reinforcement and recognition for students' effort. Fast et al. (2010) argue that the degree to which a classroom environment is perceived as challenging also influences self-efficacy. This challenge is especially necessary in the case of high ability students who, if not challenged or engaged with lessons that fit their abilities, would lose motivation in their learning (Davis, 2012). This need for challenge in student learning is supported by brain research which suggests that the brain will continue to develop only when a student is challenged (McAllister & Plourde, 2008). In addition, one way to make this environment challenging is through providing students with progressively difficult tasks as their proficiency increases. This can be provided by the teacher whose support guarantees to a greater degree the success of students in the challenge. It can be concluded from the previous argument that teacher support, if managed rightly, can help students to overcome their math anxiety (Beilock, & Willingham, 2014).

The present research intends to examine the role of teacher support in paths of variables, in order to explain how different variables, affect student effort. Here teaches support is considered an independent variable. Another variable that we want to consider as independent one is student math-level.

Student Math-Level

Another variable that we expected to influence students' learning is student math-level. Pajares and Miller (1994) found that the level of high school mathematics and number of credits earned provide a strong measure of students' prior experience with mathematics. So, we hypothesized that math level, together with teacher support are expected to affect different variables of students' learning. This effect would be in light of their math anxiety.

Math Anxiety

Dowker, Sarkar and Looi (2016) say that the construct of mathematics anxiety has been an important topic of study at least since the concept of "number anxiety" was introduced by Dreger and Aiken (1957), and has received attention since then, but increased attention in recent years.

Hembree (1990) found that in the population of school pupils, mathematics anxiety showed a mean correlation of −0.73 with enjoyment of mathematics and −0.82 with confidence in mathematics. In the population of college students, the equivalent mean correlations were a little lower than in schoolchildren, but still very high: −0.47 between mathematics anxiety and enjoyment of mathematics, and −0.65 between mathematics anxiety and confidence in mathematics. In addition to these findings of Hembree (1990), Dowker et al. (2016) argue that mathematics anxiety seems to be particularly related to self-rating, where students who think that they are bad at mathematics are more likely to be anxious. This is in line with studies that indicate a negative relationship between mathematics self-concept and mathematics anxiety (Hembree, 1990; Jain & Dowson, 2009; Hoffman, 2010). Mathematics anxiety is related to effort too. Ashcraft and Kirk (2001) reported that, across several studies, they have found substantial evidence for performance differences as a function of math anxiety. They described these differences as not observed on the basic whole-number facts of simple addition or multiplication but observed on more difficult arithmetic problems. In a more recent research, Ashcraft and Krause (2007) emphasize that math anxiety influences cognitive processing in a straightforward way, where working memory resources are compromised whenever the anxiety is aroused. Moreover, math anxiety leads to a global avoidance pattern. This is presented in the finding that, whenever possible, students avoid taking math courses and avoid situations in which math will be necessary. This avoidance pattern could explain students' unwillingness to spend effort when they are mathematically anxious.

Bandalos, Yates and Thorndike-Christ (1995) studied what factors influence math anxiety of university students. Categorizing it as general test anxiety and statistical test anxiety, they found that students' attributions for failure and success influenced both categories of anxiety for both male and female students. In more detail, women who attributed success to behavioral causes had a higher level of math self-concept than women attributing success to external causes. For men, those who attributed failure to external causes had a higher level of the worry component of statistical test anxiety. Moreover, math self-concept was negatively related to both general test anxiety and statistics test anxiety, whereas perceived self-efficacy had a negative relationship with the worry component of statistics anxiety.

Student Self-Concept in Doing Mathematics

Researchers defined self-concept as one's perception of his/her strength, weakness, state of mind, and value (Huitt, 2004; Marsh & Craven, 1997). Moreover, self-concept is influenced by our sense of identity, by our perception of social interaction and by the judgments made of us by others (Purkey & Novak, 1996, as reported by Tang, 2011). In addition, Marsh and Craven (1997) argue that enhancing a child’s academic self-concept is a desirable goal that could result in improved academic achievement. This improvement in academic achievement could be a result of academic effort, where students who perceive their academic skills positively tend to participate in more effort-oriented activities such as engaging in class activities, finishing homework, and studying for exams (Valentine, DuBois, & Cooper, 2004). Marsh, Trautwein, Ludtke, Koller and Baumert (2005) argue that the possible improvement of student performance is based on a reciprocal relationship between self-concept and academic achievement. We claim that this argument also holds for the relationship between self-concept and effort. One reason for this similarity is the reciprocal relationship between effort and achievement, where effort leads to achievement, on one hand, and on the other hand achievement encourages effort.

Wang (2007) draws our attention that professional organizations of mathematics education, as well as mathematics education researchers, have considered affective factors that self-concept is one of, as an important aspect of mathematics education. Moreover, students’ mathematics self-concept is an important outcome of education and is related to successful mathematics learning (Marsh and O’Mara, 2008). Furthermore, students who have a low level of mathematics self-concept perform worse in mathematics than students who have a higher level of mathematics self-concept.

In addition to the relationships above, Liu (2010) examined the relation between academic self-concept and motivation in foreign language learning, finding that all of the academic self-concept related variables and the motivation components are positively and significantly correlated.

Student Motivation to Learn Mathematics

Wæge (2009) argues that there has not been done much work in mathematics education on students’ motivation. Trying to define student motivation, Wæge (2009) attracts the attention to five sets of motivational factors used by Stipek et al. (1998) and that constitutes the components of achievement motivation. These five motivational factors are (1) students’ focus on learning and understanding mathematics concepts as well as on getting right answers; (2) students' enjoyment in engaging in mathematics activities; (3) students' related positive (or negative) feelings about mathematics; (4) students' willingness to take risks and to approach challenging tasks; and (5) students' self-concept as mathematics learners. In the present research, we used different questionnaires for motivation, anxiety and self-concept, where motivation was considered a construct that has external motivation and internal motivation as components. Doing so, we intend to study the associations with motivation, when the paths start from teacher support together with an individual factors, and ends in student effort.

Student Effort to Learn Mathematics

Effort is a construct that can explain differences in students' learning, including achievement. Sorensen and Hallinan (1977) categorized the factors that can explain differences in achievement among students as: learning opportunities, effort, and ability. Carbonaro (2005) commented that by focusing on learning opportunities and effort, Sorensen and Hallinan highlighted the importance of both social structure and human agency in explaining differences in learning.

Carbonaro (2005) examined the relationships among students' effort, tracking (assigning students to different classes on the basis of their achievement levels), and students' achievement. Doing so, different factors that influence student' effort were taken care of, as well as consequences of these efforts. The results indicated that students in higher tracks exerted substantially more effort than students in lower tracks. Moreover, those results indicated that differences in effort were largely explained by differences in prior effort and achievement, as well as students' experiences in their classes. Furthermore, students' effort was strongly related to students' learning.

Sullivan, McDonough and Harrison (2004) studied students' perceptions of the contribution of their effort to their success in mathematics. In more detail, they studied students' perceptions of the extent to which student' own efforts contributed to their success in mathematics and their life opportunities. They found that even students who were confident, successful and persistent in their learning exhibited short-term goals. They also found that classroom culture may be an important determinant of under participation in schooling. Furthermore, the authors concluded that the participating students seemed to have the necessary self-confidence and appreciation of the contribution of effort and persistence, but may under contributed due to characteristics of the classroom culture. Here too, we see the importance of teachers' role in the mathematics classroom, where their support is a decisive factor in the classroom culture that influences student effort.

Research Goals and Rationale

The present research intends to find possible models that consitute paths leading to student effort. Thus, the present research is about the sources of effort in mathematics learning and how these sources advance in paths that lead to student effort. Usher and Pajares (2009) studied sources of self-efficacy in mathematics. Here, we do that for effort. Usher and Pajares (2009) considered four starting points: Mastery experience, vicarious experience, social persuasions and physiological state. We too take into account the social aspect, with other individual factors. Specifically, our present research assumes that two variables start the path to performance; math level and teacher support, or self-concept and teacher support. The models also assume that additional variables are involved, as anxiety and motivation. Still there is deficit in researches that study the effect of both social and individual factors on one construct related to student learning. At the same time, few researches take into consideration both cognitive and affective factors as affecting students' effort in learning mathematics. The present research attempts to do so.

Research Question

Which Good-Fitting models can explain the effect of teacher support, math-level, anxiety, motivation and self-concept on student effort in learning mathematics?

METHOD

Participants

Seven hundred and twenty eighth, ninth and tenth students' grades completed the questionnaires. There were 381 males and 339 females. All participants were from northern West Bank in Palestine, at upper primary governmental schools.

Data Collecting Tools

The data was collected using a questionnaire that had two parts. The first part collected background information about the respondent; namely grade and gender. The second part of the questionnaire requested the respondent to choose the extent to which he/she agrees with a statement. The statements were related to 5 variables: teacher support, student self-concept, student anxiety, student motivation and student effort.

Math level was assigned according to the math grade of the teacher. Mathematics anxiety scale was taken from Morony, Kleitman, Lee and Stankow (2013). Teacher support scale was taken from Johnson, Johnson, Buckman, and Richards (1985). Mathematics self-concept scale was taken from Vandecandelaere, Speybroeck, Vanlaar, De Fraine and Van Damme, (2012). Mathematics motivation scale was taken from two categories of the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia & McKeachie, 1993): Intrinsic Goal Orientation and Extrinsic Goal Orientation. Furthermore, student effort scale was adapted from Engagement and Effort Scale (SEES) from Vallerand, Fortier and Guay (1997).

Each of the variables was represented by 8 items. Examples on the items are: the mathematics teacher spends enough time to help me when I ask him to (teacher support), I get anxious when I solve mathematical problems (anxiety), sometimes when I don't understand a mathematical topic at the beginning, I know that I will not understand it (self-concept), I try my best to get a good grade in mathematics at the end of the trimester (motivation), I study very hard to learn mathematics (effort).

Statistical Analysis

Path analysis, a type of structural equation modeling, was used to analyze the models and to evaluate their ability to fit the data. The SEM with ML procedure was used. The fitting between the hypothetical models and observed data were assessed by examining the following indexes; relative chi-square [CMIN/df], Bentler-Bonnett normed fit index [NFI], non-normed (Tucker-Lewis) fit index [TLI], comparative fit index [CFI], goodness of fit index [GFI], adjusted goodness of fit index [AGFI], and the classical root mean square error of approximation (RMSEA). (Browne & Cudeck, 1993; Byrne, 2010; Hu & Bentler, 1998; MacCallum & Austin, 2000); RMSEA is one of the most important indicators showing the degree to which estimated parameters of an SEM model are representative for the whole population from which the sample was drawn. Since RMSEA is sensitive to misspecifications of relationship among variables and it is accompanied by a confidence interval, which provides an indication of precision of estimation, its use in applied research is strongly encouraged (MacCallum& Austin, 2000). CMIN/df is also called the normed chi-square. This value equals the chi-square index divided by the degrees of freedom. This index might be less sensitive to sample size. The criterion for acceptance of the model, according to chi-square varies across researchers, ranging from more than 2 (Ullman, 2006) to less than 5 (Schumacker & Lomax, 2010). Values greater than 0.95 for GFI, AGFI, NFI, TLI and CFI, and RMSEA and value lower than 0.05 indicate a good fit of the hypothetical model to the observed data (Byrne, 2010). Following suggestions from the literature, it was considered that a value of RMSEA as high as 0.08 indicates an acceptable fit of the SEM model (Browne & Cudeck, 1993). In addition, TLI and CFI values ranging from 0.90 to 0.95 indicate an acceptable model fit (Hu & Bentler, 1998). Furthermore, some authors such as Bagozzi and Yi (2012) have used a more liberal cutoff NFI value of 0.80.

RESULTS

A correlational cross-sectional design was performed, using self-report measures, to examinine the associations among teacher support, student math-level, anxiety, motivation, self-concept, and effort in mathematics for eighth, ninth and tenth grades' students. Follwoing this design, we used Structural Equation Modeling (SEM) technique to compute each hypothesized model's fit.

Based on the literature review, the present study intended to investigate how the six psychological, individual and social variables (teacher support, math level, mathematical anxiety, mathematical motivation, self-concept, and effort) constitute a model that explains student effort in learning mathematics. Doing so, we assumed that teacher support (the social variable) would probably be an independent variable. As a second indpendent variable, we chose an individual variable. Once, we took math-level and another time we took self-concept.

Based on the previous research findings, the first model hypothesizes paths from teacher support and math-level to anxiety, motivation, and mathematical effort. It hypothesizes two paths from anxiety to mathematical effort and self-concept. It hypothesizes one path from motivation to self-concept and one path from self-concept to mathematical effort. Finally, it hypothesizes covariance between teacher support and math level. Figure 1 shows this model.

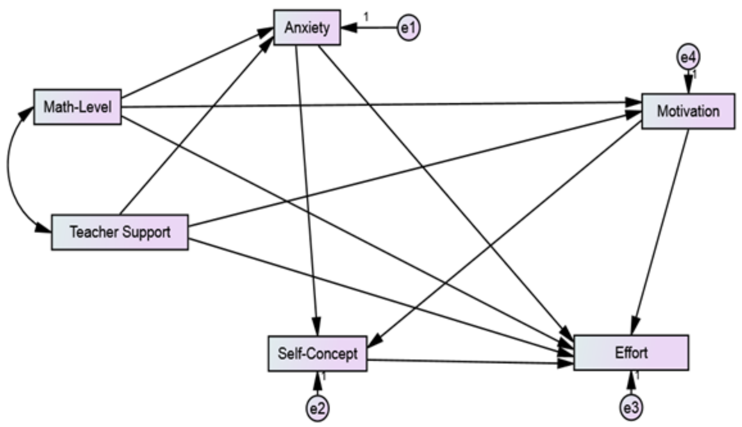

Figure 1. The first model relationships with self-concept are indirect and all paths end in effort

It could be seen that the first model hypothesizes that relationships with self-concept are not direct, where anxiety and motivation mediate them. On contrast, the second model hypothesizes that the relationships with self-concept is direct; i.e. teacher support, math level and math anxiety have direct paths with self-concept. At the same time, anxiety has a direct path with self-concept and effort, and self-concept has a direct path with effort. This model is represented in Figure 2.

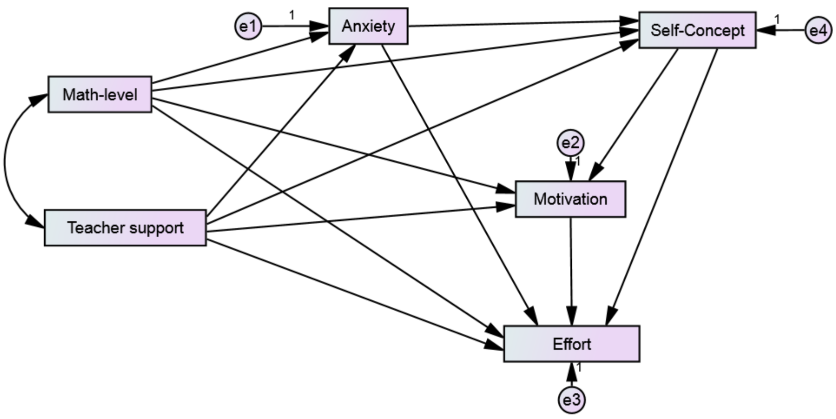

Figure1. The second model relationships with self-concept are direct and all paths end in effort

Note that the first two models assume that the five variables (teacher support, math-level, anxiety, self-concept and motivation) have direct paths to effort. Furthermore, the first model assumes a direct path from motivation to self-concept, while the second model assumes that the path is otherwise, i.e. from self-concept to motivation.

The third model hypothesizes paths from four variables, not five, to effort, where no direct path goes from self-concept to effort. A path is hypothesized to go otherwise; i.e. from effort to self-concept. This model is represented in Figure 3.

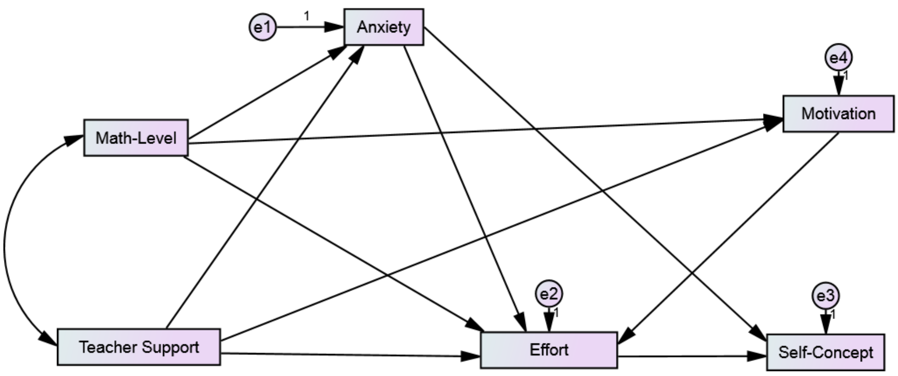

Figure 2. The third model relationships with self-concept are not direct and all paths end in self-concept

The fourth model again hypothesizes paths from four variables to effort, but the difference from the first three models is that it starts from teacher support and self-concept, where self-concept replaces math-level in the first three models. The fourth model is represented in Figure 4.

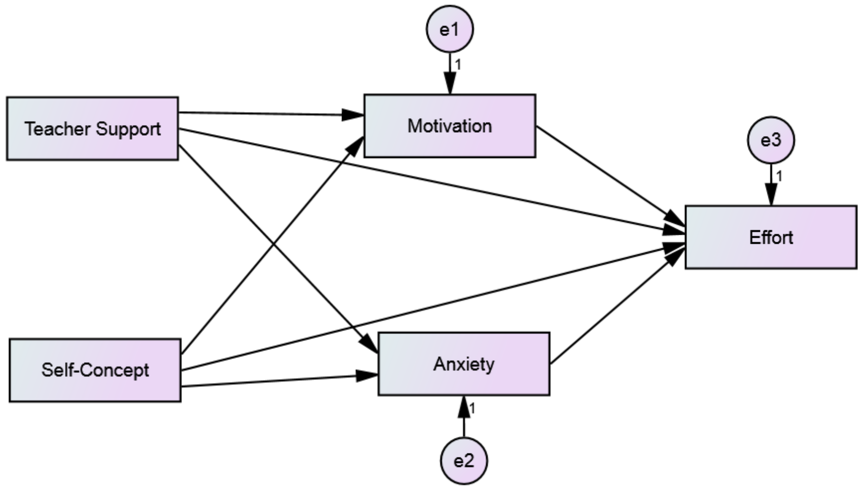

Figure 4. Self-concept is at the beginning of the model

SEM Analysis for the First Model

Statistics were performed to compute the model fit for the hypothesized first model, standardized paths coefficients, and the estimate of the variance explained (R^2). The computations showed that the χ^2 value for the hypothesized model was 10.70 (d.f. = 3, p = 0.013). So, the relative χ^2 was (CMIN/df = 3.567). Moreover, the RMSEA estimate of 0.06 (90% CI = 0.024; 0.100) succeeded in providing support for the model. Bentler's CFI was 0.993, which means the proposed model fit the data according to this index. For NFI, TLI, GFI, and AGFI, they were 0.991, 0.967, 0.995, and 0.966 respectively, so all of these values indicated the proposed model fit the data.

In the first model, R^2 = 0.296 for anxiety, 0.257 for motivation, 0.097 for self-concept and 0.544 for effort (See Figure 5 for seeing the paths for each of them). These values explain the variances explained by the first model.

According to results in table 1, all paths coefficients were significant except the path from math level to effort. In addition, the covariance coefficient between teacher support and mathematical level was significant (p = 0.273).

Table 1. Results of SEM analysis for the First Model

Parameter Description	S.E.	St. est.	P-value
Motivation from Teacher Support	0.023	0.384	0.000
Anxiety from Teacher Support	0.032	-0.18	0.000
Anxiety from Math Level	0.025	-0.466	0.000
Motivation from Math Level	0.018	0.243	0.000
Self-concept from Anxiety	0.019	0.257	0.000
Self-concept from Motivation	0.027	0.25	0.000
Effort from Motivation	0.036	0.469	0.000
Effort from Teacher Support	0.025	0.263	0.000
Effort from Anxiety	0.026	-0.146	0.000
Effort from Self-concept	0.044	0.115	0.000
Effort from Math Level	0.02	0.056	0.068
Teacher Support and Math Level	0.034	0.273	0.000

Note. S.E. – standard error; St. est. – standardized estimate.

The observed paths of the first model are presented in Figure 4.

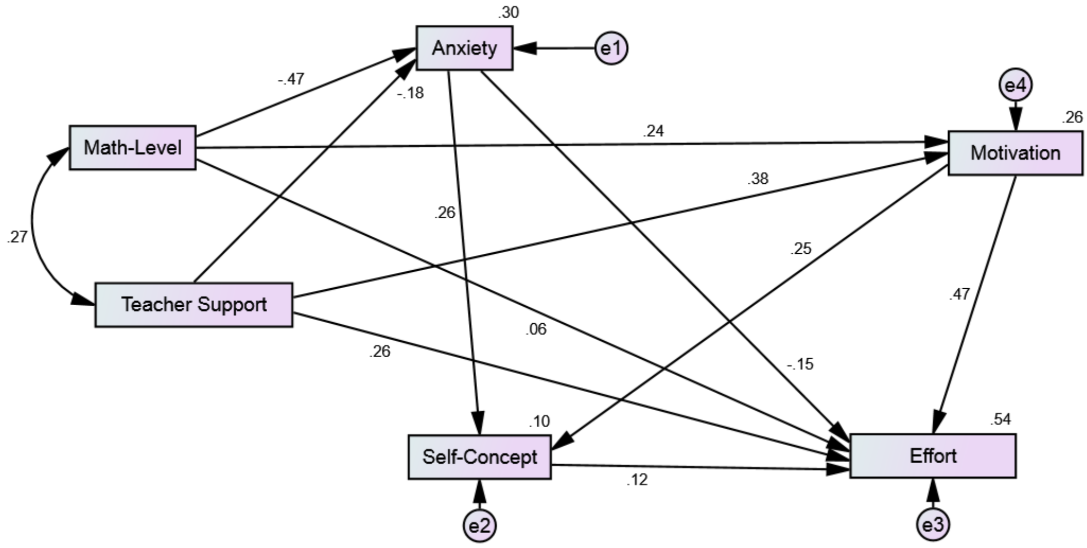

Figure 5. Observed paths of the first model

SEM Analysis for the Second Model

Statistics were performed to compute the model fit for the hypothesized second model, standardized paths coefficients, and the estimate of the variance explained (R^2). The χ^2 value for the hypothesized model was 0.615 (d.f. = 1, p = 0.433). So, the relative χ^2 was (CMIN/df = 0.615). Moreover, the RMSEA estimate of 0.03 (90% CI = 0.012; 0.053) succeeded in providing support for the model. Bentler's CFI was 0.999, which means the proposed model fit the data according to this index. For NFI, TLI, GFI, and AGFI, they were 0.999, 0.998, 0.999, and 0.978 respectively, so all of these values indicated the proposed model fit the data.

In the second model, R^2 = 0.296 for anxiety, 0.08 for self-concept, 0.287 for motivation, and 0.543 for effort (see Figure 6 for seeing the paths for each of them). These values explain the variances explained by the second model.

According to results in table 2, all paths coefficients were significant except the path from math level to effort.

Table 2. Results of SEM analysis for the second model

Parameter Description	S.E.	St. est.	P-value
Anxiety from Teacher Support	0.032	-0.18	0.000
Anxiety from Math Level	0.025	-0.466	0.000
Self-concept from Anxiety	0.022	0.326	0.000
Self-concept from Teacher Support	0.02	0.133	0.000
Self-concept from Math Level	0.017	0.146	0.000
Motivation from Teacher Support	0.023	0.371	0.000
Motivation from Self-concept	0.043	0.172	0.000
Motivation from Math Level	0.018	0.244	0.000
Effort from Teacher Support	0.025	0.263	0.000
Effort from Anxiety	0.027	-0.146	0.000
Effort from Self-concept	0.044	0.116	0.000
Effort from Motivation	0.036	0.469	0.000
Effort from Math Level	0.021	0.056	0.070
Teacher Support and Math Level	0.034	0.273	0.000

Note. S.E. – standard error; St. est. – standardized estimate.

The observed paths of the second model are presented in Figure 6.

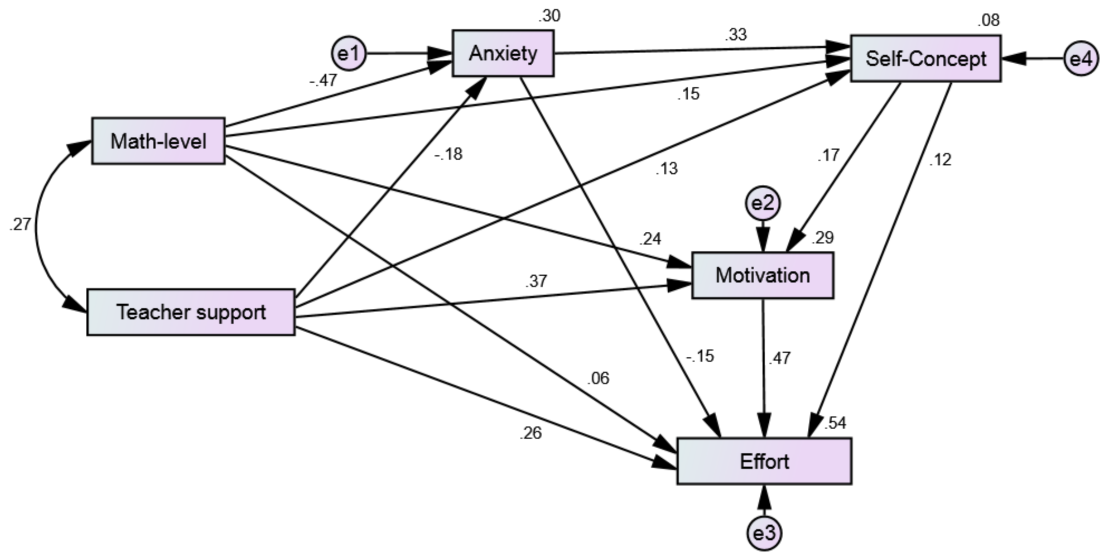

Figure 6. Observed paths of the second model

SEM Analysis for the Third Model

Statistics were performed to compute the model fit for the hypothesized third model, standardized paths coefficients, and the estimate of the variance explained (R^2). The χ^2 value for the hypothesized model was 13.617 (d.f. = 4, p = 0.009). So, the relative χ^2 was (CMIN/df = 3.404). Moreover, the RMSEA estimate of 0.058 (90% CI = 0.013; 0.003) succeeded in providing support for the model. Bentler's CFI was 0.992, which means the proposed model fit the data according to this index. For NFI, TLI, GFI, and AGFI, they were 0.988, 0.969, 0.994, and 0.967 respectively, so all of these values indicated the proposed model fit the data.

R^2 for anxiety = 0.296, for motivation = 0.257, for self-concept = 0.119 and for effort = 0.533 (see Figure 7 for seeing the paths for each of them). These values explain the variances explained by the third model.

According to results in table 3, all paths coefficients were significantexcept the path from math level to effort.

Table 3. Results of SEM analysis for The Third Model

Parameter Description	**S.E.**	**St. est.**	**P-value**
Motivation from Teacher support	0.023	0.384	***
Anxiety from Teacher support	0.032	-0.18	***
Anxiety from Math Level	0.025	-0.466	***
Motivation from Math Level	0.018	0.243	***
Effort from Motivation	0.036	0.492	***
Effort from Teacher support	0.025	0.269	***
Effort from Anxiety	0.026	-0.11	***
Effort from Math Level	0.021	0.066	0.033
Self-concept from Anxiety	0.02	0.305	***
Self-concept from Effort	0.023	0.299	***
Teacher support and Math Level	0.034	0.273	0.000

The observed paths of the third model are presented in Figure 7.

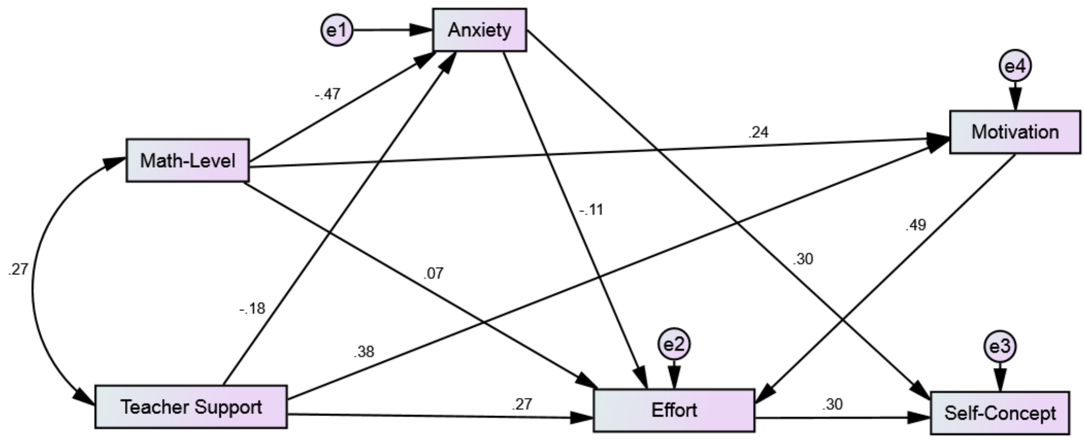

Figure 7. Observed paths of the third model

SEM Analysis for the Fourth Model

Statistics were performed to compute the model fit for the hypothesized fourth model, standardized paths coefficients, and the estimate of the variance explained (R^2). The $\chi2$ value for the hypothesized model was 3.848 (d.f. = 1, p = 0.05). So, the relative $\chi2$ was (CMIN/df = 3.848). Moreover, the RMSEA estimate of 0.063 (90% CI = 0.002; 0.135) succeeded in providing support for the model. Bentler's CFI was 0.997 for the present model, which means the proposed model fit the data according to this index. For NFI, TLI, GFI, and AGFI, they were 0.996, 0.967, 0.998, and 0.968 respectively, so all of these values indicated the proposed model fit the data.

R^2 for anxiety = 0.16, for motivation = 0.22 and 0.53 for effort (see Figure 8 for seeing the paths for each of them). These values explain the variances explained by the fourth model.

According to results in table 5, all paths coefficients were significant.

Table 1. Results of SEM analysis for the fourth Model

Parameter Description	S.E.	St. est.	P-value
motivation from teacher support	0.023	0.44	0.000
Anxiety from self-concept	0.066	0.23	0.000
Anxiety from teacher support	0.034	-0.32	0.000
motivation from self-concept	0.044	0.17	0.000
effort from motivation	0.035	0.48	0.000
effort from anxiety	0.024	-0.18	0.000
effort from teacher support	0.025	0.27	0.000
effort from confidence	0.044	0.12	0.000
Correlation between e1 and e2	0.015	-0.11	0.005

Note. S.E. – standard error; St. est. – standardized estimate.

The observed paths of the fourth model are presented in Figure 8.

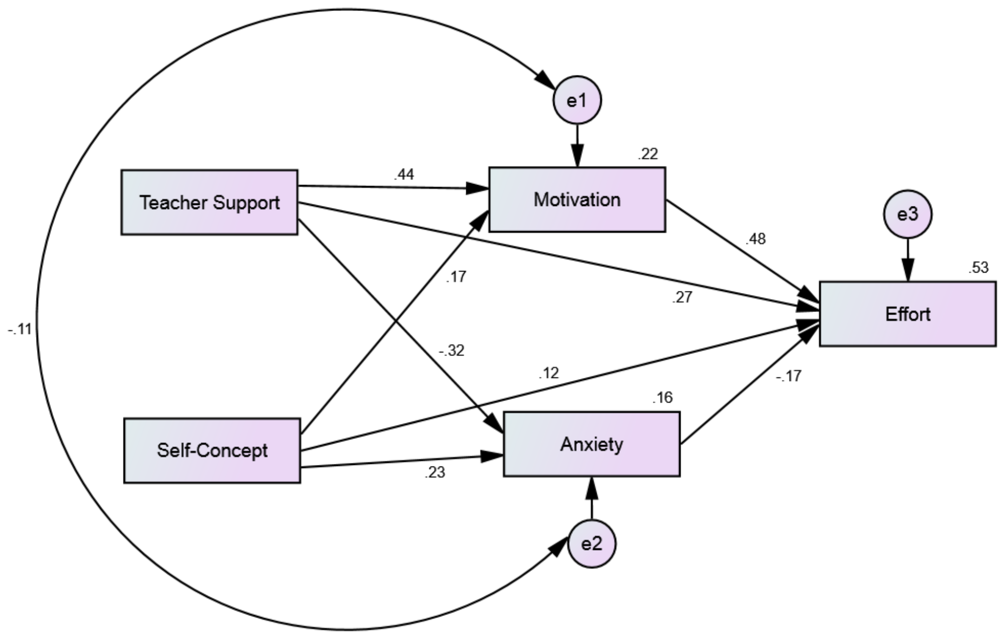

Figure 8. Observed β-s of the fourth model

DISCUSSION

The present research intended to study the factors that affect student effort to learn mathematics. To do so it examined five variables as factors that could affect this student effort: teacher support, student math level, anxiety, motivation, self-concept. Different models were hypothesized for the paths between the six variables of the present research. The models were hypothesized based on two starting conditions: teacher support is one of the variables that start the paths, and student effort is the variable that ends the paths.

Path analysis served as structural equation modeling for analyzing the models and to evaluate their ability to fit the data. The first model assumed that teacher support and math-level affect directly and indirectly (through motivation, anxiety and self-concept) student effort in learning mathematics. This model explained 0.544 for effort scores, with the limitation that math-level did not have a significant direct path with student effort. The insignificant path could be explained by the possibility that students attempt to perform in mathematics regardless of their math level. This attempt could be encouraged by the teacher support. This role of the teacher depends on his/her expectations, caring, and support, where these functions to set the tone for student behavior (Baker, 1999; Noddings, 1992). This role of the teacher is represented in the first model through the significant paths from teacher support to student motivation, and at the same time, from student motivation to student effort. Thus, it could be argued that teacher support sets the tone for student motivation, which leads to his/her greater effort in learning mathematics. In addition, it could be claimed that math-level affected student effort indirectly through anxiety and self-concept, where the appropriate paths were significant.

The second model has two differences with the first model; the paths from teacher support and math-level to self-concept are direct and self-concept leads to motivation and not otherwise. These two differenced did not make the model better. The model explained 0.543 of the variance for effort scores, and the direct path from math-level to effort was still insignificant. Still, it could be argued that math-level affected significantly student effort indirectly as could be seen from the significant the following significant paths: math-level to anxiety and anxiety to effort, math-level to motivation and motivation to effort, math-level to self-concept and self-concept to effort. In addition, the previous research results of the insignificant path between math level and effort should be looked at in light of other researches results that mathematics ability had a direct effect on mathematics performance (e.g., Zarch & Kadivar, 2006). Zarch and Kadivar (2006) also found that math level had an indirect effect on performance via mathematics self-efficacy judgments. This indirect effect, of math-level on effort, was also found in the present research, where the mediating variables were anxiety, motivation and self-concept.

The third model, in light of the limitations of the first two models, examined what happens if self-concept replaces effort. This model explained 0.533 of the variance of effort, but the more important result was that all the paths between the variables turned to be significant, including the path from math-level to effort. This could mean that the model that neglects self-concept as a mediating factor that leads to effort could be sounder than other models that try to explain effort. This does not contradict past studies that found that self-concept leads to effort (Fiore, 1999), for the present research findings describe a model and not a simple relationship. The third model's Fit-computations made us examine a model in which self-concept is an independent variable, together with teacher support. This was our fourth model. Fit computations of the fourth model resulted in significant paths of the model, where it explained 0.53 of the variance of student effort.

Based on the results, the most appropriate models to explain the data were the third and fourth models, where all paths in these two models were significant. Furthermore, they explained moderately the variance of effort, where 0.30 < R squared < 0.60 is considered moderate (Sanchez, 2013). These models are most appropriate though they considered self-concept differently, where the third model considered self-concept a dependent variable, at the end of the model, while the fourth model considered it an independent variable, at the beginning of the model. These results show the importance of the configuration of the model. They also show the centeredness of self-concept as a construct that affects learning in the mathematics classroom, where in certain setting it affects learning as an independent variable, and in other setting, it affects learning as a dependent variable through affecting the configuration that leads to student effort.

CONCLUSIOLNS

The present research results show that educational phenomena are compound, so we need to examine how the variables of these phenomena impact each other. In the present research, we used Path analysis, a type of structural equation modeling, to verify the factors that influence student effort in the mathematics classroom. Results showed that paths leading from teacher support, as a social variable, and math-level of self-concept as an individual variable, to student effort could constitute different models. Specifically, self-concept has a special role in such model, where it could be considered an independent or dependent variable. These results constitute important findings in the field for previous reason; i.e. the impact of self-concept on students' learning of mathematics, where this impact varies among different educational configurations. We, as educators, should pay attention to what educational variables we are attending and encouraging first, for our choice of the educational constructs that we attend to first will impact the outcome of the actors' processes in the educational setting.

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