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A Self-Regulation Model of Mathematics Achievement for Eleventh-Grade Students

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Abstract
In recent years, mathematical thinking and reasoning have been widely discussed to promote students' abilities to apply mathematical knowledge and ideas in their daily living. However, few studies have investigated the role of self-regulation in relation to reasoning. This study examined the effects of self-regulation processes on student mathematical reasoning and academic achievement. Using a quantitative research design and the PLS-SEM technique, data were collected from 248 private school students in Malaysia. The PLS-SEM results showed that behavioral regulations, including processes of self-observation, self-judgment, and self-reaction, are decisive factors in influencing student academic achievement and student mathematical reasoning ability. The dimensions of motivational regulation, including processes of self-efficacy, task value, and mastery goal orientation, are dominant factors influencing student reasoning ability, followed by cognition regulation, which includes use of elaboration strategy and critical thinking skills. The study also found that cognition regulation is a significant mediator of the relationship between motivational regulation and reasoning ability. Behavioral and cognition regulation processes, as well as students' reasoning ability, are the mediators of motivational regulation on academic achievement. The results of this study suggest that teachers should foster the adoption of self-regulation processes in mathematics learning.

Keywords Behavioral · Cognition · Motivational · PLS-SEM · Reasoning · Self-regulation

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Introduction

Mathematics skill is a powerful tool which can also be applied in daily life. Learning mathematics is important as it will help students to have better reasoning, analytical thinking, decision making abilities, and communication skills. In addition, mathematics skill helps students to make better sense of the world around them and possibly solve daily life problems. Nevertheless, mathematics teaching and learning present challenges. First, students' interest in learning mathematics has declined over the years (Davadas & Lay, 2018; Ng, Liu, & Wang, 2016). Second, instead of focusing on procedural or algorithmic applications, mathematics communities have called for reform to increase students' mathematical literacy, defined as "the ability to apply mathematics to analyse, reason and communicate effectively as they pose, solve and interpret mathematical problems in a variety of situations" (National Council of Teachers of Mathematics [NCTM], 2009, p. 3).

To cope with this change in focus in mathematics teaching, there is emerging literature proposing the inclusion of self-regulation in student learning. Self-regulation theorists regard self-regulation as an integral part of the learning process consisting of any actions, behaviors, and/or strategies learners take to facilitate their learning. Students are more likely to initiate efforts to acquire knowledge if they are self-regulated learners (Pintrich, 2004; Zimmerman, 2002). A significant number of studies have revealed that self-regulation has a positive association with academic achievement (e.g. Fadlelmula, Cakiroglu, & Sungur, 2015; Mousoulides & Philippou, 2005; Velayutham & Aldridge, 2013; Zimmerman, 2002). In fact, individual learning abilities may vary depending on the level of self-regulation skills (Velayutham & Aldridge, 2013). In particular, highly self-regulated students are more likely to be motivated and capable of using a repertoire of strategies as compared to low self-regulated students (Mousoulides & Philippou, 2005; Parvin, Vahid, & Gholamreza, 1998).

Despite the development of the self-regulation field and the creation of self-regulation models, Dent and Koenka's (2016) meta-analysis uncovered different definitions of the construct as well as research methodologies resulting in different key self-regulation components and their relative importance in their respective research domain. Many previous studies have mainly focused on a subset of self-regulation strategies from the perspectives of cognitive and/or metacognitive strategies with motivational beliefs or other learning aspects on students' academic achievement (e.g. Azar, Lavasani, Malahmadi, & Amani, 2010; Fadlelmula et al., 2015; Keskin, 2014; Li, Zheng, Liang, Zhang, & Tsai, 2018; Mason, Boscolo, Tornatora, & Ronconi, 2013; Mousoulides & Philippou, 2005; Rashid & Hashim, 2008; Velayutham & Aldridge, 2013; Vogt, Hocevar, & Hagedorn, 2007; Wu, 2005; Yang, 2012). Relatively few studies have focused on the interaction of behavioral regulation with motivational and cognition regulations. However, Zimmerman (2002) found that these processes are the main performance-related processes significantly related to academic achievement. Other scholars (e.g. Iskender, 2009; Lan, 1996; Mayer, 1998; Ramdass & Zimmerman, 2008) contend that motivational factors are interrelated with behavioral regulation and, ultimately, improved academic achievement.

Students' mathematics achievement has always been reported based on a scoring system. Debate continues about which aspects of student thinking are unidentifiable from these scores (Schoenfeld, 2016). High academic achievement does not necessarily equate with good critical thinking skills (Verawati, Arifin, Idris, & Hamid, 2010). High test scores do not necessarily indicate that students learn meaningfully and with understanding (Danisman & Erginer, 2017). For these reasons, Schoenfeld (2016) has called for studies on student performance in four areas of proficiency: concepts and procedures, problem-solving, reasoning, modeling, and data analysis. However, previous self-regulation studies in mathematics have mainly focused on academic achievement rather than mathematical reasoning. There is a lack of empirical examples comparing and contrasting the role of self-regulation on mathematics achievement from two aspects: mathematical reasoning performance and academic achievement.

Indeed, according to Brodie (2010), mathematical reasoning not only requires students to examine task constraints but also requires self-regulation and self-monitoring. Schoenfeld (2016, p. 508) stated the "difficulties with monitoring and self-regulation (aspects of metacognition) could cause problem-solving failure, despite individuals having the knowledge to solve problems." Thus, self-regulation in mathematics learning is important in promoting student understanding of mathematical knowledge. When students regulate and monitor their own thinking process, they are more likely to integrate existing knowledge with new mathematical relationships (Brodie, 2010).

This paper contributes to the literature by examining a self-regulation model of mathematical reasoning performance and academic achievement based on Zimmerman's (1989) triadic analysis of self-regulation grounded in social cognitive theory. In this model, the level of self-regulation depends on three general aspects of learning, namely behavioral regulation, motivational regulation, and cognition regulation. Behavioral regulation refers to one's proactive control and use of various strategies or resources to attain learning goals. Motivational regulation refers to covert processes such as self-efficacy, task value, and goal orientation initiated by individuals to influence other processes. Cognition regulation refers to one's proactive selection and use of various cognitive strategies such as critical thinking skills and elaboration strategy to store and retrieve information. These general aspects of self-regulation are assumed to be interrelated in a self-regulatory system (Zimmerman, 1989, 2002).

Previous self-regulation research depends heavily on quasi-experimental design or qualitative design. Relatively few studies have explored the causal-effects of various self-regulation components on mathematics achievement by using partial least squares structural equation modeling (PLS-SEM). Because of the several statistical advantages of PLS-SEM approach over covariance-based SEM (CB-SEM), PLS-SEM has become a popular multivariate analysis technique in recent years (Duarte & Amaro, 2018; Hair, Hult, Ringle, & Sarstedt, 2014, 2017). PLS-SEM is a prediction-oriented approach, primarily focused on explaining the variance in the dependent variables when examining the model, whereas CB-SEM is primarily used to confirm theories, aimed at reproducing the theoretical covariance matrix.

Despite the PLS-SEM approach having been widely used by many researchers in various disciplines including accounting, information systems, marketing, human resource management, business management, and tour management in recent years (Latan, 2018), its use in mathematics education is still in the exploratory stage. Evidence is limited to only a few studies on self-regulation in mathematics using CB-SEM (e.g. Azar et al., 2010; Fadlelmula et al., 2015; Mousoulides & Philippou, 2005).

To resolve this issue, this paper contributes to the research literature on self-regulation in mathematics by using a higher order model or hierarchical component model (HCM) approach in PLS-SEM. The HCM approach helps to create multidimensional constructs. It involves summarizing lower-order components (LOC) into a single multidimensional higher-order construct (HOC). For example, several motivational factors can be summarized into a single HOC named motivational, several cognitive strategies can be summarized into a single HOC named cognition, and so on. These models reduce complexity and enable future research to increase the content comprised by specific HOCs (Duarte & Amaro, 2018). So far, based on our knowledge, there is no study using the HCM approach to define a multidimensional self-regulation model of mathematical achievement.

In this article, we show how we apply PLS-SEM techniques to the study self-regulation in mathematics, provide evidence of the validity of this approach in understanding student mathematics achievement, and determine specific forms of self-regulation that best predict both mathematical reasoning performance and academic achievement.

Research Model and Hypotheses

This study conceptualizes the research model based on a triadic analysis of self-regulation (Zimmerman, 1989). This theory posits that student learning outcomes are influenced by three main regulation processes: motivational (MOT), behavioral (BEH), and cognition (COG). The model shows how these regulation processes positively impact students' mathematical reasoning ability (MR) and their academic achievement (AP).

Our literature review revealed that students need to be motivated in order to manage a sufficient amount of effort to accomplish assigned tasks (Weinstein, Husman, & Dierking, 2000). Therefore, perceived self-efficacy beliefs, task value, and mastery goal orientation play significant roles in initiating and maintaining an individual's level of motivation self-regulation (Velayutham & Aldridge, 2013). Self-efficacy (SE) refers to "judgments of competence to perform a task"; task value (TV) refers to "beliefs about the importance, utility, and relevance of the task"; and mastery goal orientation (MGO) refers to "purposes for doing task" (Pintrich, 2004, p. 395). Many empirical studies have shown that self-efficacious students are more motivated to learn, and those who see a task as exciting and valuable are more likely to increase their mastery performance, ultimately leading to academic success (Zimmerman, 2002).

According to Zimmerman (2002), students tend to employ various learning strategies to attain learning goals. These learning strategies generally help students to organize and reconstruct their knowledge (Weinstein et al., 2000). In general, cognitive psychologists refer these learning strategies as cognitive strategies that self-regulated students use to facilitate their learning (Borich & Tombari, 1996). Cognitive strategies are important because they help students “select and control personal behaviors in attending to the learning situation, managing the memory and recall systems and organizing the learning problem or solution” (Wilson & Weinstein, 1989, p. 137). They are also involved in improved memory, reading comprehension, and mathematics problem-solving (Borich & Tombari, 1996). Thus, highly self-regulated students tend to use various cognitive strategies with purposes, cognized goals, and strategic planning.

Of these cognitive strategies, elaboration strategy and critical thinking skills are widely discussed in the literature. Critical thinking skills (CTS) refer to deep cognitive strategies used to devise alternative solutions, questions, reflection, and mathematical thinking. Elaboration strategy (ELA) is used to extract and summarize main ideas, connecting, relating, and applying mathematical knowledge by pulling together the acquired information from different resources to facilitate mathematical reasoning. Previous studies have shown that elaboration strategy and critical thinking skills affect academic achievement (Bayat & Tarmizi, 2010).

Triadic analysis of self-regulation theory posits that self-regulated students should not only know how to use a cognitive strategy, but they must be able to regulate it. This means students should know how to plan, monitor, and approach activities in a strategic way (Weinstein et al., 2000). Therefore, students need self-observation capability. Self-observation (SO) is a key process in the control phase to track an individual’s cognitive functions. This process refers to any behaviors, beliefs, or actions that can be used to monitor one’s learning progress. In particular, self-monitoring is a “covert form of self-observation” (Zimmerman, 2002, p. 68). According to Weinstein et al. (2000), when students are aware of when to use appropriate strategies in their learning, they are said to possess metacognition—knowledge about their own cognition. Hence, they will have clearer ideas on what they are currently doing to complete the task (Panadero & Alonso-tapia, 2014).

Further, Zimmerman (2002) stated that self-regulated students will regulate self-reflection after each assigned learning task. These learning processes involve self-judgment and self-reaction. Self-judgment (SJ) refers to self-regulated students will self-evaluate their performance against their personal standards or criteria. Self-reaction (SR) refers to students attribute their failures to maladaptive strategies used, which lead them to greater self-satisfaction and more willingness to put efforts in improving performance (Zimmerman, 2002). When students experience greater self-satisfaction, their motivation will increase, resulting in adaptive reactions and assured learning effectiveness (Zimmerman, 2002). These feedbacks contribute significantly to their future strategy use in similar tasks.

Figure 1 operationalizes these components as lower-order constructs (LOCs) and higher-order constructs (HOCs), demonstrating a multidimensional model of self-regulation used in this study.

In the model, latent constructs (i.e. variables that are not directly measured) are represented as circles and indicators (i.e. manifested variables) are represented as rectangles. The relationship between an indicator and a latent construct can be expressed as reflective or formative. In the reflective measurement model, all of the relevant indicators are considered to be functions of the latent construct (i.e. arrow of the latent construct is pointing to its respective indicators), whereas formative

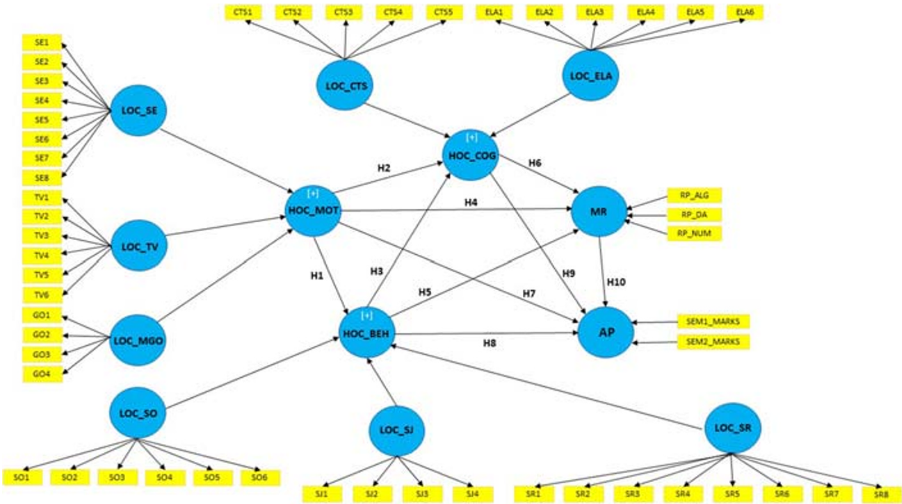

Fig. 1 The multidimensional model of self-regulation

measurement indicators are assumed to be directed at a latent construct (i.e. arrows of the indicators are pointing to its latent construct).

Figure 1 operationalizes lower order constructs (LOC_SE, LOC_TV, LOC_MGO, LOC_ELA, LOC_CTS, LOC_SO, LOC_SJ, and LOC_SR) as reflective measurement models (i.e. dropping one of the indicators would not alter the conceptual domain of the LOC as indicators have similar content). Speficically, LOC_SE was measured by 8 indicators (SE1 to SE8), LOC_TV was measured by 6 indicators (TV1 to TV6), LOC_MGO was measured by 4 indicators (GO1 to GO4), LOC_ELA was measured by 6 indicators (ELA1 to ELA6), LOC_CTS was measured by 5 indicators (CTS1 to CTS5), LOC_SO was measured by 6 indicators (SO1 to SO6), LOC_SJ was measured by 4 indicators (SJ1 to SJ4), and LOC_SR was measured by 8 indicators (SR1 to SR8).

As for higher order constructs (HOC_MOT, HOC_COG, and HOC_BEH), they have formative measurements because their LOCs are defining characteristics of the HOC, which means dropping one of the LOCs would alter the conceptual domain of the HOC. Specifically, HOC_MOT consisted of LOC_SE, LOC_TV, and LOC_MGO; HOC_COG consisted of LOC_ELA and LOC_CTS; and HOT_BEH consisted of LOC_SO, LOC_SJ, and LOC_SR. Likewise, latent construct MR and AP were operationalized as formative measurement. MR consisted of 3 indicators (RP_ALG, RP_NUM, and RP_DA) and AP consisted of 2 indicators (SEM1_MARKS and SEM2_MARKS).

Therefore, there were ten direct effects identified from the proposed model. Accordingly, the present study formulated the following hypotheses:

H1: Motivational regulation (HOC_MOT) has positive effect on behavioral regulation (HOC_BEH).

H2: Motivational regulation (HOC_MOT) has positive effect on cognition regulation (HOC_COG).

H3: Behavioral regulation (HOC_BEH) has positive effect on cognition regulation (HOC_COG).
H4: Motivational regulation (HOC_MOT) has positive effect on mathematical reasoning performance (MR).
H5: Behavioral regulation (HOC_BEH) has positive effect on mathematical reasoning performance (MR).
H6: Cognition regulation (HOC_COG) has positive effect on mathematical reasoning performance (MR).
H7: Motivational regulation (HOC_MOT) has positive effect on academic achievement (AP).
H8: Behavioral regulation (HOC_BEH) has positive effect on academic achievement (AP).
H9: Cognition regulation (HOC_COG) has positive effect on academic achievement (AP).
H10: Mathematical reasoning performance (MR) has positive effect on academic achievement (AP).

In addition, the proposed research model also hypothesized the following indirect effects:

H11: Behavioral regulation (HOC_BEH) mediates the relationship between motivational regulation (HOC_MOT) and cognition regulation (HOC_COG).
H12: Behavioral regulation (HOC_BEH) and/or cognition regulation (HOC_COG) mediate the relationship between motivational regulation (HOC_MOT) and mathematical reasoning performance (MR).
H13: Behavioral regulation (HOC_BEH), cognition regulation (HOC_COG) and/or mathematical reasoning performance (MR) mediate the relationship between motivational regulation (HOC_MOT) and academic achievement (AP).

Research Methodology

Sample and Procedure

Relatively few studies have focused on upper level secondary students; most have involved primary, junior secondary, or university students. Most of the self-regulation theorists contend that students' self-regulatory behavior may vary according to their background and contextual factors (Pintrich & de Groot, 1990; Zimmerman, 2002). Therefore, we selected 248 eleventh-grade students (aged between 17 and 18 years old) from a private secondary school located in Klang, Malaysia. This school has mixed-ability class settings and was selected due to its accessibility. The sample included 109 males and 139 females.

This study utilized a quantitative research design and the PLS-SEM technique to test the path relationships of the proposed constructs discussed in the previous section. The study met the sample size requirement suggested by Hair et al. (2014, 2017), which is 10 times the largest number of formative indicators used to measure a single construct or 10 times the largest number of structural paths directed at a construct in the structural model. As shown in Fig. 1, the largest number is four structural paths directed at construct AP in the structural model, indicating a minimum of 40 cases. In this study, the participants were asked to complete a mathematical reasoning test and fill out a questionnaire survey after the test.

Measures

Instrument 1: a Questionnaire

The questionnaire consists of questions pertaining to perceived self-efficacy, mastery goal orientation, task value, elaboration strategy, and critical thinking skills which adapted from the Motivated Strategies for Learning Questionnaire (MSLQ) (Artino, 2005), whereas self-observation, self-judgment, and self-reaction toward mathematics were adapted from Wu (2005). The measures for these variables were anchored on a 7-point Likert scale (1 = not at all true of me to 7 = very true of me).

Instrument 2: Mathematical Reasoning Test

The reasoning test consisted of nine short structured questions adapted from the National Assessment of Educational Progress (NAEP) released items (National Center for Education Statistics, n.d.). Each question is allocated 5 marks. Therefore, students' mathematical reasoning performance (MR) was measured by three indicators: (a) RP_ALG: sum scores of 3 questions which assessed student understanding of Algebra; (b) RP_NUM: sum scores of 3 questions which assessed students in number properties and operations; and (c) RP_DA: sum scores of 3 questions which assessed students in statistics content.

Instrument 3: School Semester Examinations

The students sit for two compulsory semester examinations for mathematics subject in an academic year (over 100 marks). Therefore, the students' academic achievement (AP) was measured by two indicators: (a) SEM1_MARKS: first semester examination (b) SEM2_MARKS: second semester examination.

Data Analysis and Results

We used *SmartPLS 3* software (Ringle, Wende, & Becker, 2015) to test the research hypotheses. PLS-SEM runs the PLS algorithm (path weighting scheme, stop criterion value of 1×10^{-7}, maximum of 300 iterations) to estimate the parameters of the model (e.g. factor loadings, weights, path coefficients) and a non-parametric bootstrapping procedure (5000 subsamples, no sign changes, bias-corrected and accelerated [BCa bootstrap], two-tailed test, 5% significance level) to determine the significance levels for the estimated parameters. Before the relationships of the proposed latent constructs were assessed, validity and reliability of the measurement models were tested.

Common Method Bias

In studies in which both independent and dependent variables are measured from the same participants, researchers suggest that the data be assessed according to whether it is affected by common method variance (CMV) (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In this study, Harman's single-factor test was used to evaluate CMV. Results indicated that the restricted extraction of a single factor explained 33.92% of the variance. This is less than the 50% threshold that constitutes a CMV effect.

Assessment of Reflective Measurement Models

The outer variance inflation factors (VIFs) of the manifested indicators were examined prior to assessment of the reflective measurement models. The purpose was to avoid problems with multicollinearity. To do this, the indicators for SE2, SE5, and GO2, with VIF values more than the cutoff point of 5, were omitted. In a PLS-SEM context, researchers should assess indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability indicates variance of the indicator that can be explained by the underlying latent construct; it should be at least higher than the recommended value of .70 (Hair et al., 2014). Therefore, indicators for SR7 and SR8 with factor loadings less than .70 were omitted. Table 1 shows all the retained indicators that had factor loadings higher than .70 ($p < .005$).

For evaluation of the internal consistency reliability of a latent construct, Latan (2018) argued that using composite reliability is too liberal. Hence, he recommends researchers to report Cronbach's alpha or Dijkstra-Henseler's rho (ρ_A). However, Hair et al. (2014) argued that Cronbach's alpha assumes that all indicators are equally reliable and sensitive to the number of items in the scale. Thus, they suggest that researchers report composite reliability (CR). Taking both arguments into consideration, the present study used Cronbach's alpha, ρ_A, and CR to assess internal consistency reliability of the reflective constructs. The values appearing in Table 1 show that all reflectively measured constructs in the study had Cronbach's alpha, ρ_A, and CR values higher than the recommended value of .70 ($p < .005$).

As for convergent validity, average variance extracted (AVE) is used to measure the extent to which the average variance of the indicators is explained by an underlying latent construct. Table 1 shows the AVE values for all reflectively measured constructs that were higher than the recommended value of .50 ($p < .005$).

For discriminant validity, researchers are encouraged to use the heterotrait-monotrait ratio of correlations (HTMT) instead of the Fornell-Larcker criterion or cross-loadings as both are substantially over-estimated and biased in measuring discriminant validity (Hair et al., 2017; Latan, 2018). Table 2 shows that all HTMT ratios were below the recommended value of .85 and significant at .005 levels, thus indicating that all reflectively measured constructs met the requirement for discriminant validity.

Table 1 Indicator reliability, internal consistency reliability, and convergent validity of reflective measurement models

Constructs	Indicators	Factor loadings	Cronbach's alpha	rho_A	CR	AVE
LOC_SE	SE1	.887	.933	.935	.948	.751
	SE3	.887				
	SE4	.823				
	SE6	.820				
	SE7	.874				
	SE8	.905				
LOC_MGO	GO1	.890	.847	.852	.907	.765
	GO3	.883				
	GO4	.851				
LOC_TV	TV1	.737	.920	.926	.938	.716
	TV2	.831				
	TV3	.888				
	TV4	.891				
	TV5	.861				
	TV6	.857				
LOC_SO	SO1	.823	.920	.922	.937	.714
	SO2	.893				
	SO3	.843				
	SO4	.871				
	SO5	.850				
	SO6	.787				
LOC_SJ	SJ1	.916	.927	.929	.948	.821
	SJ2	.907				
	SJ3	.918				
	SJ4	.883				
LOC_SR	SR1	.768	.916	.919	.935	.708
	SR2	.880				
	SR3	.906				
	SR4	.907				
	SR5	.823				
	SR6	.750				
LOC_ELA	ELA1	.850	.911	.914	.931	.693
	ELA2	.862				
	ELA3	.868				
	ELA4	.805				
	ELA5	.781				
	ELA6	.827				
LOC_CTS	CTS1	.796	.842	.850	.888	.614
	CTS2	.841				
	CTS3	.758				
	CTS4	.810				
	CTS5	.707				

Assessment of Formative Measurement Models

Constructs for MR and AP are two formatively measured first-order constructs in the research model (see Fig. 1). In the PLS-SEM context, researchers should assess values

Table 2 Discriminant validity of reflective constructs

Constructs	LOC_CTS	LOC_ELA	LOC_MGO	LOC_SE	LOC_SJ	LOC_SO	LOC_SR
LOC_ELA	.739						
LOC_MGO	.703	.615					
LOC_SE	.623	.531	.812				
LOC_SJ	.392	.396	.333	.265			
LOC_SO	.361	.309	.253	.294	.600		
LOC_SR	.370	.435	.459	.491	.439	.507	
LOC_TV	.641	.585	.838	.746	.362	.299	.376

of indicator weight, indicator significance, and VIF value to assess collinearity issues. Table 3 shows that all formative indicators had indicator weights higher than .10 and were significant at .005 levels, except for indicator SEM1_MARKS. Although the outer weight for indicator SEM1_MARKS was insignificant, its factor loading was high (i.e. .895); hence, the indicator was retained for the measurement model, as recommended by Hair et al. (2014). All formative indicators had VIF values less than 5; these confirmed that the indicators were free from multicollinearity issues.

Assessment of Higher Order Constructs

Three formatively measured HOCs were formulated in the research model, HOC_MOT, HOC_BEH, and HOC_COG (see Fig. 1). In the PLS-SEM context, a few approaches have been proposed to assess the HOCs (i.e. repeated indicator approach, two-stage approach, and hybrid approach) (Duarte & Amaro, 2018). In the research model, HOC_BEH and HOC_COG were endogenous constructs. Duarte and Amaro (2018) suggest these types of models can be assessed using the two-stage approach as it does not require an equal number of indicators for the LOCs when HOCs are in endogenous constructs.

During the first stage of this study, the quality of the reflectively measured LOCs was assessed according to their quality criteria as discussed in the above section (see section Assessment of Reflective Models). To estimate the path coefficients of the HOCs, at the second stage, each HOC was formatively represented by the latent variable scores (LVS) of its respective LOCs obtained from the first stage. LVS is estimated as "exact linear combinations of their associated manifest variables," also

Table 3 Assessment of formative measurement models for first-order constructs

Constructs	Indicators	Weights	Sig.	Loadings	VIF values
MR	RP_ALG	.516	.000	.792	1.205
	RP_DA	.409	.000	.720	1.201
	RP_NUM	.412	.000	.721	1.200
AP	SEM1_MARKS	.273	.217	.895	2.950
	SEM2_MARKS	.766	.000	.987	2.950

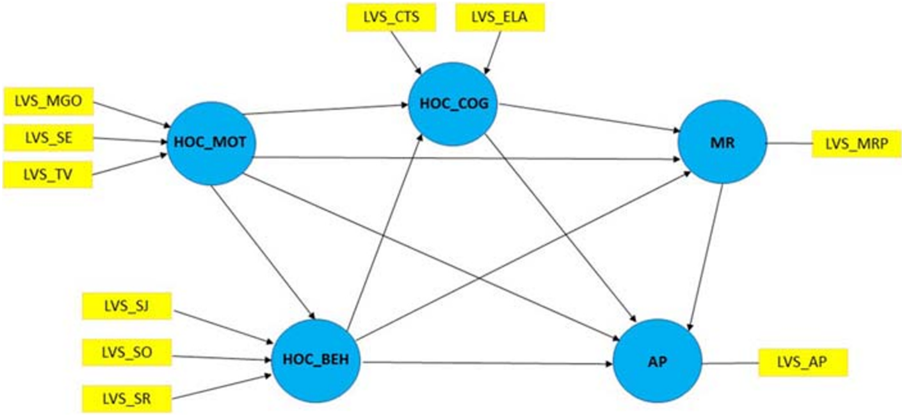

Fig. 2 The second stage of formative higher order constructs

referred to factor or composite scores (Monecke & Leisch, 2012, p. 2). Because constructs MR and AP were conceptualized as a first-order construct at the first stage, these constructs resulted in a single LVS items at the second stage (see Fig. 2). The assessment of relations between LVSs and its construct was applied per Duarte and Amaro (2018).

To estimate the quality of HOCs, the indicator weight, indicator significance, and VIF value for the respective HOC were determined. Table 4 shows that all the formative indicators' weights of their respective HOC were higher than the recommended value of .10 and significant at .005 levels, except for indicator LVS_SO and LVS_SJ, which were significant beyond .10 levels.

However, both LVS_SO and LVS_SJ revealed a high factor loading (i.e. LVS_SO = .735 and LVS_SJ = .711). They were retained in the model because the loading factor is interpreted as being fundamentally important. In addition, the VIF values of all indicators were less than the threshold value of 5, an indication of the absence of multicollinearity among the constructs.

Table 4 Assessment of formative higher order constructs

Constructs	Indicators	Weights	Sig.	Loadings	VIF values
HOC_MOT	LVS_SE	.398	.002	.901	2.373
	LVS_MGO	.337	.004	.905	2.802
	LVS_TV	.373	.002	.902	2.573
HOC_BEH	LVS_SO	.253	.090	.735	1.623
	LVS_SJ	.298	.065	.711	1.510
	LVS_SR	.664	.000	.906	1.343
HOC_COG	LVS_ELA	.395	.002	.853	1.771
	LVS_CTS	.694	.000	.955	1.771

Table 5 Collinearity assessment of the structural model

Constructs	HOC_BEH	HOC_COG	MR	AP
HOC_MOT	1.000	1.277	1.919	2.028
HOC_BEH		1.277	1.338	1.339
HOC_COG			1.886	1.929
MR				1.229

Assessment of Structural Model

The inner VIF values between measured constructs were assessed to detect any collinearity issues before path coefficients of the relationships were estimated. Table 5 shows that inner VIF values between the constructs were less than the recommended value of 5, indicating no multicollinearity issues in the structural model.

To estimate the standardized path coefficients of the model, this study applied the bootstrapping procedure with 5000 resamples. Table 6 shows the significance of path relationships in the research model. The study also evaluated the effect size f^2 of each significant path relationship in the structural model. Effect size f^2 values of .02, .15, and .35 indicate that an exogenous construct has a small, medium, or large effect on an endogenous construct. Predictive relevance of the model is assessed by R^2 values and Stone-Geisser's Q^2 values. The R^2 values of .02, .13, and .26 indicate weak, moderate,

Table 6 Assessment of structural model

	Path relationships	Direct effects	Total indirect effects	Total effects	VAF (%)	f^2	R^2	Q^2
H1	HOC_MOT ➔ HOC_BEH	.466**		.466**		.277	.217	.110
H2	HOC_MOT ➔ HOC_COG	.583**	.083*	.667**		.502	.470	.361
H3	HOC_BEH ➔ HOC_COG	.179*		.179*		.047		
H11[a]	HOC_MOT ➔ HOC_BEH ➔ HOC_COG		.083*		12.44			
H4	HOC_MOT ➔ MR	.298**	.111*	.410**		.057	.187	.157
H5	HOC_BEH ➔ MR	−.030	.034	.003		.001		
H6	HOC_COG ➔ MR	.188*		.188*		.023		
H12[a]	HOC_MOT ➔ HOC_COG ➔ MR		.110*		26.83			
H7	HOC_MOT ➔ AP	−.126	.317**	.191**		.011	.259	.225
H8	HOC_BEH ➔ AP	.398**	−.002	.396**		.159		
H9	HOC_COG ➔ AP	−.015	.065*	.050	16.41	.000		
H10	MR ➔ AP	.347**		.347**		.132		
H13[a]	HOC_MOT ➔ HOC_BEH ➔ AP		.185**		96.86			
H13[a]	HOC_MOT ➔ HOC_COG ➔ MR ➔ AP		.038*		19.90			
H13[a]	HOC_MOT ➔ MR ➔ AP		.103**		53.93			

*$p < .05$; **$p < .005$

[a] Specific indirect effect

and substantial predictive accuracy, respectively. The model is considered to have predictive relevance if Q^2 is greater than zero (Hair et al., 2014, 2017).

The results revealed a significant relationship between motivational and behavioral regulation processes with medium to large effect ($\beta = .466$, $p < .005$, $f^2 = .277$). Motivational regulation moderately explained the prediction of behavioral regulation (i.e. $R^2 = .217$, $Q^2 = .110$). Both motivational and behavioral regulations were found to predict cognition regulation at a significant level (HOC_MOT ➔ HOC_COG: $\beta = .583$, $p < .005$, $f^2 = .502$; HOC_BEH ➔ HOC_COG: $\beta = .179$, $p < .05$, $f^2 = .047$). However, the effect sizes differed; while motivational regulation on cognition regulation is large, the effect size of behavioral regulation on cognition regulation is considerably smaller. Nevertheless, behavioral regulation was found to mediate the relationship between motivational and cognition regulations (HOC_MOT ➔ HOC_BEH ➔ HOC_COG: $\beta = .083$, $p < .05$). The strength of an indirect effect can be explained by the variance accounted for by the mediator (VAF: ratio of indirect effect to total effect). In this study, behavioral regulation explained 12.44% of the relationship between motivational and cognition regulations. Both motivational and behavioral regulations accounted for 47% of the variances in explaining cognition regulation; this is considered to be substantial.

In terms of predicting students' performance in mathematical reasoning, both motivational and cognition regulations were revealed as having significant effects. This was not the case for behavioral regulation (HOC_MOT ➔ MR: $\beta = .298$, $p < .005$, $f^2 = .057$; HOC_COG ➔ MR: $\beta = .188$, $p < .05$, $f^2 = .023$). Cognition regulation partially mediated the relationship between motivational regulation and mathematical reasoning performance with a VAF value of 26.83%, indicating that 26.83% of the effect of motivational regulation on students' mathematical reasoning was explained through their cognition regulation. These constructs moderately explained 18.7% of the variances in the construct MR.

On the contrary, behavioral regulation and students' mathematical reasoning ability significantly predicted academic achievement. This was not the case for motivational and cognition regulations (HOC_BEH ➔ AP: $\beta = .398$, $p < .005$, $f^2 = .159$; MR ➔ AP: $\beta = .347$, $p < .005$, $f^2 = .132$). Though both direct effects of motivational and cognition regulations on academic achievement were statistically insignificant, their indirect effects were found to be significant beyond .05 levels, especially for indirect effects of motivational regulation on academic achievement. More specifically, behavioral regulation fully mediated the relationship between motivational regulation and students' academic achievement with a high VAF value of 96.86%. The analysis also showed that 53.93% of the effects of motivational regulation on students' academic achievement were explained through their mathematical reasoning ability. In addition, cognition regulation and students' mathematical reasoning ability were found to be significant sequential mediators that mediated the relationship between motivational regulation and academic achievement with a small effect (i.e. VAF = 19.90%). These constructs accounted for 25.9% of the variances in explaining students' academic achievement; this is considered to be substantial.

Discussion and Conclusion

Summary of Findings

Past studies have generally focused on a combination or subset of various self-regulation processes on students' mathematics achievement. This is the first study of which we are aware that involves an evaluation of the significance of the multidimensionality of self-regulation on students' mathematical reasoning and academic achievement. Our results, obtained via the administration of three instruments to nearly 250 high school students, led to development of a multidimensional self-regulation model, based on Zimmerman's (1989) triadic analysis, to identify specific dimensions of self-regulation that appear to affect students' mathematical reasoning and academic achievement.

Consistent with the theory, we found that motivational, cognition, and behavioral regulation processes are significantly interrelated with student learning. Motivational regulation directly contributes to behavioral regulation with a medium to high effect and cognition regulation with a high effect. This indicates that students with higher levels of motivational regulation are more likely to use deep learning strategies to facilitate their learning and attain their academic goals. Therefore, our study confirms that students' self-regulation level is affected by motivational, behavioral, and cognition aspects.

In this study, we have shown that behavioral regulation is the most dominant dimension for students' academic achievement but not for mathematical reasoning. Of the behavioral regulation processes, self-reaction stands out among the other two processes; this shows that students with greater self-satisfaction are more likely to engage in adaptive learning. This contradicts the findings of Fadlelmula et al. (2015), who found that planning, monitoring, and regulating as the metacognitive self-regulation strategies relate negatively and not significantly related to mathematics achievement. The findings of the current study are based on social cognitive theory whereby self-observation, self-judgment, and self-reaction processes are the three main performance-related behavioral processes. However, these processes are more relevant to academic achievement than they are to mathematical reasoning. Apart from that, mathematical reasoning performance was the second decisive factor in influencing students' academic achievement. This suggests that students who are proficient in reasoning skills are likely to perform well in their mathematics learning.

The results of motivational regulation have been found to be inconsistent throughout the literature. For instance, Mousoulides and Philippou (2005) reported self-efficacy as being related to mathematics achievement, but Fadlelmula et al. (2015) found self-efficacy unrelated to mathematics achievement. Vogt et al. (2007) reported that self-efficacy was related to students' GPA. This may possibly be due to the majority of previous studies focusing on the sole motivation factor (i.e. self-efficacy) in their models. Although Azar et al. (2010) included self-efficacy, task value, and mastery goal orientation in their estimation, they linked self-efficacy directly to students' mathematics achievement, but they did not link achievement to task value and mastery goal orientation. These different conceptualizations of the model (e.g. Azar et al., 2010; Fadlelmula et al., 2015; Li et al., 2018; Mousoulides & Philippou, 2005) have produced different results, consequently limiting the comprehensive view of the self-regulation model.

In this study, we found that the three sub-dimensional factors of motivational regulation, self-efficacy, task value, and mastery goal orientation do not have a direct effect on student academic achievement. At the same time, we found both direct and indirect effects of motivational regulation on students' mathematical reasoning. We also found that behavioral regulation, cognition regulation, and mathematical reasoning ability are possible mediators in the relationship between motivational regulation and students' academic achievement. Evidently, students' motivational regulation is insufficient to initiate proactive learning but positive behaviors and use of appropriate cognitive strategies are required to facilitate the learning process.

In addition, cognition regulation was found to be directly related to students' mathematical reasoning but an indirect predictor of students' academic achievement. Cognition regulation enhances the relationship between motivational regulation and students' mathematical reasoning. Of deep learning strategies, critical thinking skills contribute to higher weights for cognition regulation as compared to use of elaboration strategy. This indicates that students with higher critical thinking skills are more likely to perform better in reasoning and academic achievement.

In conclusion, the results of this study show that behavioral, motivational, and cognition regulations contribute both to achievement and mathematical reasoning. This suggests that processes need to be integrated into the learning process to facilitate students' academic achievement and their mathematical reasoning.

Theoretical Implications

This study validated a multidimensional self-regulation model on students' academic achievement and mathematical reasoning performance. The model shows a distinct difference between the dimension of behavioral and motivational regulation. Behavioral regulation is the decisive factor in students' academic achievement, followed by their mathematical reasoning ability, whereas motivational regulation is the dominant factor in influencing students' mathematical reasoning ability, followed by cognition regulation.

The study also provides evidence to support the partial mediation between cognition regulation and motivational regulation and students' mathematical reasoning ability. In addition, the research model confirmed that behavioral regulation, cognition regulation, and mathematical reasoning ability fully mediate the relationship between motivational regulation and students' academic achievement. Specifically, behavioral regulation exhibits the largest mediating effect of motivational regulation on academic achievement, followed by students' mathematical reasoning ability. Cognition regulation and students' mathematical reasoning were found to sequential mediators in enhancing students' academic achievement with a small mediating effect. The model concurred with Zimmerman's triadic analysis, whereby the dimensions of cognition, motivational, and behavioral regulations are interdependent in a self-regulation model.

Practical Implications

Student learning is affected by personality, behavior and environmental factors. Improving students' positive behaviors in learning is a key concern, as these behaviors mediate the relationship between students' motivational beliefs and their academic achievement. Based on the results of this study, we suggest that teachers identify opportunities for students to self-observe their work progress, self-evaluate their learning outcomes, and self-react to adaptive learning. When students monitor their task process, they are more likely to self-evaluate learning outcomes. These positive behaviors help enhance students' awareness in the use of appropriate deep learning strategies (i.e. critical thinking skills) as well as support their motivation in solving mathematical reasoning problems. When students experience success, they will attain greater academic achievement.

Research conducted by Tee, Leong, and Abdul Rahim (2018) found that use of the critical thinking skills was the dominant predictor of students' mathematical reasoning ability. In that context, we suggest that teachers implement strategies that help their students maximize the search for optimal problem solutions. To build students' confidence and ability to solve reasoning problems, teachers can promote sense-making in alignment with recent recommendations (NCTM Research Committee, 2011). Use of elaboration strategies may increase the likelihood of sense-making activity (Brodie, 2010).

Limitations and Future Research Directions

The present study was limited to exploring the causal-effect of a multidimensional self-regulation model on students' mathematical reasoning and academic achievement. Each dimension consists of various self-regulation processes and how these processes predict students' mathematical reasoning and academic achievement. To have a comprehensive view of the interrelationships among the processes, one should conceptualize these processes separately. Though the research model of this study cannot be generalized to each subfactor, it would be helpful if future researchers can add in more components under a corresponding dimension to compare if there are any discrepancies between influencing students' mathematical reasoning and academic achievement. Given that students' levels of self-regulation may vary due to different background, culture, or classroom settings, it is suggested that this model can be used for future in-depth self-regulation studies and to broaden the scope of research on students' reasoning skills.

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