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Mathematics and Performance in Mathematics Literacy: The Relation Between Intrinsic Motivation to Learn Mathematics, Mathematics Anxiety, and Cognitive Activation as a Mediator

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Mathematics and Performance in Mathematics Literacy: The Relation Between Intrinsic Motivation to Learn Mathematics, Mathematics Anxiety, and Cognitive Activation as a Mediator

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Abstract

Researchers have conducted numerous studies on the positive effects of intrinsic motivation to learn mathematics and the negative impact of mathematics anxiety on students' performance in mathematics literacy. The study examined how the introduction of cognitive activation in mathematics lessons, a mediator variable, would alter these effects between the independent and dependent variables. We used structural equation modeling to analyze data. This study examined data from 2012 for 4500 Australian students. Participants were between 15 and 16 years old. The first model analyzed the entire data set, the second model considered gender, and the third model focused on students' socioeconomic status. The whole sample showed a positive correlation between intrinsic motivation to learn mathematics, cognitive activation, and performance in mathematics literacy, irrespective of gender and students' socioeconomic status. The whole sample showed a negative correlation between mathematics anxiety, cognitive activation, and performance in mathematics literacy. For the whole sample, the independent variables (mathematics anxiety and intrinsic motivation) partially mediate the cognitive activation in mathematics lessons.

Introduction

Beginning in the 1960s, researchers in the field of education have been examining the correlation between emotions and cognition. For about half a century, researchers have extensively examined the impact of emotional phenomena on the process of acquiring mathematical knowledge. Given the importance of mathematics, scholars have conducted numerous investigations to examine the factors influencing students' performance in this field, and ongoing research is currently in progress. Among the extant literature, Hembree (1990) emphasized that anxiety has emerged as the predominant determinant of emotional problems since the 1970s. As a result, mathematics anxiety has a significant impact on students' attainment of mathematical knowledge (Sentürk, 2010). The existence of mathematical anxiety does not necessarily impede the acquisition of mathematical proficiency. Research indicates that a moderate level of mathematics anxiety has a positive impact on students who possess inherent motivation rather than leading to any form of functional impairment (Wang et al., 2015). Therefore, the association between moderate mathematics anxiety and intrinsic motivation could enhance students' mathematical proficiency and foster their enjoyment in the learning process. Therefore, it is crucial for mathematics education to consider the mathematical proficiency of students when deciding the suitable levels of complexity (Davis & Sengupta, 2020).

While enhancing children's overall understanding is a top aim for districts, states, and the federal government, there is a specific emphasis on raising the percentage of kids who choose to seek qualifications in mathematics and science (Gastón, 2011). Schools, states, and the federal government are all striving toward the same goal: strengthening students' knowledge and skills across the board, focusing on raising the proportion of students seeking degrees in mathematics and sciences (Gastón, 2011). Regrettably, many new first-year college students, despite the potential high earnings in STEM disciplines, lack adequate preparation for postsecondary academic challenges (Reilly, Neumann, & Andrews, 2015; Siraj-Blatchford & Nah, 2014; Stoet, Bailey, Moore, & Geary, 2016).

Dailey (2009) stated that high school graduates require a better understanding of content knowledge in STEM and improved study skills to succeed in college. Similarly, high school students who are not intrinsically motivated (self-driven) to succeed often need help adjusting to postsecondary academic challenges (Braver et al., 2014; Dailey, 2009; Pitsia, Biggart, & Karakolidis, 2017). Academics have recently focused much attention on mathematics anxiety, defined as "a feeling of tension, apprehension, or fear" toward math-related activities (Ashcraft, 2002, p. 181), due to its negative correlation with students' emotional outcomes, academic performance, and overall health and wellness (Dowker et al., 2016; Ramirez et al., 2018). An unfavorable connection was found in previous meta-analyses studies between students' mathematical anxiety and their performance in mathematics (e.g., Hembree, 1990; Ma, 1999; Namkung et al., 2019; Zhang et al., 2019).

Cognitive activation inspires students to develop their unique approaches to problem solving. For example, cognitive-activation instructional techniques assist children with various learning difficulties (Braver et al., 2014; Cantley et al., 2017; Maloney et al., 2014). Cognitive activation strategies help students think more critically while solving problems. Some of these strategies include asking students to explain how they came to their conclusions and giving them opportunities to try new ways to solve math and science problems. Several studies (Ashcraft, 2002; Braver et al., 2014; Fortsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016) and anecdotal evidence from teachers and students have shown that cognitive-activation strategies increase students' intrinsic motivation and success in math classes.

Researchers have linked the application of cognitive-activation strategies in teaching to improved academic outcomes, particularly in the STEM disciplines (Baumert et al., 2010; Braver et al., 2014; Cantley et al., 2017). In addition, researchers have also shown that teaching using cognitive activation strategies boosts students' confidence when confronted with challenging mathematical and scientific tasks (Artemenko, Daroczy, & Nuerk, 2015; Halpern et al., 2007; Maloney et al., 2014). Yet, there is insufficient evidence to show cognitive activation in the classroom reduces mathematical fear (OECD, 2014). However, there are few studies exploring how cognitive-activation strategies mediate between mathematics anxiety and intrinsic motivation and affect students' performances in mathematics literacy. Furthermore, it is crucial to take into account the student's gender and socioeconomic status as potential moderators of this routing model, as research has demonstrated that these factors significantly influence children's arithmetic performance and their responses to setbacks (Stoet et al., 2016).

Theoretical Framework

Expectancy – Value Theory

Motivation drives action. Unlike those who lack motivation, motivated people are energetic and active to achieve their goals. Effective motivation is essential in all social interactions, be it in professional, educational, or recreational settings. Educational professionals, supervisors, and executives must carefully consider the advantages and disadvantages of promoting or discouraging students, employees, or followers. To alleviate these challenges, most theories consider motivation as a constant rather than a continuum (Ryan & Deci, 2000). This study explores a common motivation theory with expectations and ideals. It investigates students' academic goals and values from a broader social cognitive perspective in personality, social, and developmental psychology. Expectations and values establish the parameters of this framework (Eccles et al., 1983).

Expectations are personal assessments of skills and anticipated outcomes from new endeavors. Failure predictors are less inclined to try or persist. While individuals may appreciate the activity, they will only finish it if they keep failing and expect more (Eccles & Wigfield, 2020). According to Schunk (2004), "values" are defined as the underlying motivations that drive individuals to do action. Values are motivating factors. Personal interest, perceived relevance or utility, the promise of positive reinforcement (e.g., grades or points), the desire to please parents or professors, the fear of negative repercussions, and so on might inspire a student to finish an assignment. Expectancy-value motivation theories predict students' decisions, behaviors, and outcomes based on students' and instructors' expectations and values. Students may think they can achieve, but they won't enroll if they don't love it. Some students think their job is exciting or necessary; however, they won't do it if they fail. Knowing human motivation involves knowing its causes (Schunk, Meece, & Pintrich, 2013; Eccles et al., 1983). Assigning value to achievement can help prevent the potentially severe psychological consequences of failure.

The cognitive expectation-value theory explains human motivation. The school influences students' ideas and expectations. Low academic expectations impact students' motivation and attitudes. The expectancy-value theory posits that education influences students' expectations and values, thereby elucidating their motivation. If students don't believe they will succeed, they lose motivation. Expectations and values may predict success. Individual cognitive perspectives differ from explicit decisions and actions related to achievement. This is due to the importance placed on providing answers to questions such as "Why should I complete this task?" 2005 (Eccles). However, the question "Am I competent to do this task?" is often asked.

Literature Review

To improve students’ performance in mathematics literacy, teaching mathematics should go beyond proficiency in numerical calculations. Teaching should address other aspects that encourage or hinder students' interest in mathematics. Teachers should focus their pedagogical content knowledge of mathematics on addressing the gender gap in mathematics anxiety (MA) and low intrinsic motivation (IM) to learn mathematics. Mathematics anxiety adversely affects more girls than boys (Dowker, Sarkar, & Looi, 2016; Novak & Tassell, 2017; Stoet, Bailey, Moore, & Geary, 2016a, 2016b; Stuart, 2016). Gender-motivation research has examined self-efficacy, confidence, learning outcomes, learner goals, interests, and values. Girls and boys see math and engineering differently. Some studies find no gender disparities in technical fields, whereas others do. Most studies show that girls and women are less confident in their specialized talents, less engaged in science, and more egalitarian than males. Boys and men are more interested in STEM occupations than girls and women, although women are more community-minded than males (Diekman & Steinberg, 2013; Stolk, Gross, & Zastavker, 2021).

On the other hand, learning mathematics through IM is positively associated with improved mathematical literacy (ML) performance (Areepattamannil, 2013, 2014; Garon-Carrier et al., 2016a, 2016b). However, girls tend to have lower IM to learn mathematics than boys (OECD, 2014). A survey within the Organization for Economic Co-operation and Development (OECD) member nations (over 35 countries) revealed that 58% of boys and 49% of high school girls expressed interest in the mathematical concepts they learn. Additionally, 42% of boys and 35% of girls surveyed reported doing mathematics because they enjoyed the subject (OECD, 2014).

Cognitive activation (CA) in mathematics lessons teaches students strategies to use when solving mathematical problems (Baumert et al., 2013). Utilization of CA strategies in mathematics lessons refers to a combination of various factors, such as the teacher's competency and beliefs about teaching, ability to keep students engaged with the subject, class management skills, and innovative delivery of subject content for the optimum benefit of supporting students with diverse learning needs and styles (Baumert et al., 2013). Application of CA strategies in mathematics lessons tends to help students reduce the effects of learning challenges such as a lack of motivation to learn mathematics, mathematics anxiety, and students' lack of self-confidence in their abilities to solve mathematics problems (OECD, 2014). Therefore, the study included CA as a mediator between independent variables (MA and IM for mathematics learning) and a dependent variable (performance in mathematics literacy). Furthermore, the study investigated the indirect effects of the relations between independent and dependent variables in the presence of CA. For instance, the study aimed to determine whether the inclusion of CA altered the direct effects of MA and IM on mathematics literacy performance.

Students' Intrinsic Motivation (IM) to Learn Mathematics

Motivation is an individual incentive or form of enthusiasm that makes a person behave in a particular manner (Murayama, Pekrun, Lichtenfeld, & vom Hofe, 2013; Pitsia, Biggart, & Karakolidis, 2017; Tella, 2007). There are various types of motivation, such as instrumental, extrinsic, and intrinsic (Chang et al., 2016; Garon-Carrier et al., 2016a; Tella, 2007). "Instrumental motivation to learn mathematics is the interest to learn mathematics because students perceive it as useful to them and their future studies and careers" (OECD, 2014). For example, students may pursue mathematics because plans for their future endeavors involve the application of mathematical concepts, or they may assume that learning mathematics will enable them to advance their career interests. Students' positive image of the ideal self, external influence, positive attitude towards a subject, and the enjoyment of learning a subject are some of the factors that inspire instrumental motivation among students (Dailey, 2009; Middleton & Spanias, 1999; Pitsia et al., 2016; Tella, 2007).

Ryan and Deci (2000) point out that "because intrinsic motivation results in high-quality learning and creativity, it is essential to detail the factors and forces that engender versus undermine it" (p. 55). Liu, Hau, & Zheng (2018) define intrinsic motivation (IM) as a person's passion for an initiative or initiatives they undertake, anticipating a reward once they achieve the task's objective. For example, an intrinsically motivated student will work hard on science, technology, engineering, and mathematics (STEM) courses to increase their chances of getting into an engineering school. Extrinsic motivation is a tendency to participate in activities to earn rewards from external sources (Areepattamannil, 2013). The reward(s) could involve financial compensation, praise, or fame. A statistically significant positive association exists between students' intrinsic motivation and academic achievements (Dailey, 2009).

This study focused on IM in learning mathematics. IM is defined as enthusiasm for, drive to carry out, or a person's participation in a task because they are interested in it and enjoy performing it (Murayama et al., 2013; Ryan & Deci, 2000). Additionally, participants derive pleasure and satisfaction from engaging in the task. IM to learn mathematics refers to the level of interest and satisfaction students experience when they engage with mathematics (OECD, 2014). IM to learn mathematics encourages using in-depth learning strategies among students (Murayama et al., 2013). Such learning strategies involve a student's deliberate efforts to understand course content rather than applying surface-learning strategies. According to Murayama et al. (2013), surface learning involves memorizing information for test-taking, fear of academic failure, and an unwillingness to explore beyond fundamental course requirements. Murayama and colleagues' longitudinal study compared the relationship between IM and extrinsic motivation (engaging in a task because of an external reward or incentive) and students' mathematics performance. The study found that the long-term relationship between IM and mathematics achievement was significant and positive ($\beta = 0.54$). According to Areepattamannil (2014), who investigated the link between extrinsic motivation and students' achievement in mathematics, the relationship between extrinsic motivation and students' achievement in mathematics was significantly negative ($\beta = -0.18$).

IM to learn mathematics decreases with age (higher grades) as mathematics content becomes more complex and abstract, or as students discover their "passion in life," which may not necessarily involve learning math (Garon-Carrier et al., 2016a). In addition, high school adolescents' interest in and motivation to undertake mathematics and science study declines significantly (Kiemer, Gröschner, Pehmer, & Seidel, 2015). The cited reason for the decline is a mismatch between high school students' anticipated majors in college and actual high school teaching practices.

Finally, nurturing and sustaining student IM increases the likelihood of academic success (Dailey, 2009). According to Dailey, intrinsically motivated students are self-driven, derive enjoyment from and experience fulfillment in pursuing their goals, and are likely to expand and continue their studies beyond the stipulated course content. In addition, IM and CA's interplay in mathematics classrooms is typical in learning and performance (OECD, 2014). Therefore, this study included the IM variable for mathematics learning to assess its strengths and weaknesses in relation to other variables. Ryan and Deci (2000) indicated that most of the things that individuals do are not, strictly speaking, driven by intrinsic factors, even though intrinsic motivation is undeniably significant. This is particularly true during early infancy, when an individual's ability to be genuinely driven is already limited by the time and effort they must devote to fulfilling the expectations and duties of their many social positions. For instance, the promotion to higher grades appears to diminish students' intrinsic drive.

Mathematics Anxiety (MA)

MA is defined as fear, panic, or tension experienced by an individual (student) whenever they encounter an arithmetic problem (Ashcraft, 2002; Stoet et al., 2016b; Zhang, Zhao, & Kong, 2019). MA distracts students from focusing on numerical tasks (Artemenko, Daroczy, & Nuerk, 2015; Kargar et al., 2010a; Kargar, Tarmizi, & Bayat, 2010b). Although the negative link between MA and student ability to focus on numerical tasks is evident, there are inconsistencies among students experiencing higher MA levels (elementary, middle school, high school, or postsecondary). A metadata study that analyzed the findings of 84 studies conducted between 2000 and 2009 with a sample of 8,680 students found that female students experience higher levels of MA than their male counterparts (Zhang et al., 2019). Generally, females experience higher anxiety levels than males (Dowker et al., 2016; Stoet & Bailey, Moore, & Geary, 2016b). However, after controlling for other anxieties, such as test anxiety, female and male students' MA levels are comparable (Dowker et al., 2016; Stoet et al., 2016a). Likewise, boys' and girls' MA levels are the same in elementary school (Harari, Vukovic, & Bailey, 2013).

The effects of MA on students manifest in various ways (Lazarides, Rubach, & Ittel, 2017; Sherman & Wither, 2003). A country's education system and cultural orientation may contribute to students' levels of MA (Stoet et al., 2016a; Zhang et al., 2019). For example, students in Asian (South Korean, Singapore, and China) countries tend to experience a higher level of MA than students in Europe (Finland) and North America (OECD, 2014). Several factors contribute to the differences in MA levels among students in Asia, Europe, and North America. First, educational systems in Asian countries are more rigorous than Europe and North America (Liu et al., 2018). Second, in Asia, there is a relatively higher parental expectation about student academic performance in science, technology, engineering, and mathematics (STEM) and more significant peer pressure on students to excel in those subjects than in Europe and North America (OECD, 2014).

A study on MA cited students' age as a factor (Harari, Vukovic, & Bailey, 2013b). Early detection of negative side effects of MA, such as fear, worry, or lack of self-confidence when working with numbers, can occur in elementary school (Harari et al., 2013). According to Harari and colleagues, the effects of MA are not pronounced in the early years of schooling but become more noticeable in later years of middle school, high school, or postsecondary education. High expectations for students to excel on standardized tests, as well as the fear of failure, increase MA among high school and postsecondary students (Dowker et al., 2016; Harari et al., 2013; Harari, Vukovic, & Bailey, 2013; Kargar et al., 2010b; Maloney, Sattizahn, & Beilock, 2014; Stoet et al., 2016b; Zhang et al., 2019). Students who experience MA are likelier to lack self-confidence in their abilities to do mathematics, hold a negative attitude towards mathematics, and have unruly behavior in mathematics classes (Ashcraft, 2002; Kargar et al., 2010a). In summary, MA negatively affects students' abilities to learn mathematics.

Therefore, teachers and other stakeholders in education should try different approaches to minimize the negative effects of MA on students. This study uses cognitive activation in mathematics lessons as a mediator between MA and mathematics performance. In addition, cognitive activation in mathematics lessons tends to reduce the effects of mathematics anxiety on students (Baumert et al., 2013).

Cognitive Activation (CA) in Mathematics Lessons

According to Baumert and colleagues (2013), CA in mathematics lessons involves teaching strategies to students that they can apply when solving mathematics problems. In mathematics lessons, CA involves a set of teaching strategies, such as thinking through various ways of solving a problem instead of memorizing how to solve it (OECD, 2014). Additionally, the use of CA strategies in mathematics lessons is positively and significantly associated with improved student achievement in mathematics and other subjects (Artemenko, Daroczy, & Nuerk, 2015; Baumert et al., 2013; Förtsch, Werner, von Kotzebue, & Neuhaus, 2016; Weisseno & Landwehr, 2015). According to the OECD (2014), CA strategies in mathematics lessons benefit girls and low-SES students more than their counterparts. When using CA strategies in mathematics lessons, girls and low SES students are more likely to develop self-confidence in their abilities to do mathematics independently (OECD, 2014). Additionally, girls and low SES students experience higher MA levels than boys and high SES students (Adimora, Nwokenna, Omeje, & Eze, 2015; Stoet et al., 2016b; Zhang et al., 2019). CA strategies in mathematics lessons lower MA overall and generally improve student attitudes toward mathematics (OECD, 2014).

Teachers who use CA strategies in mathematics lessons ask students to explain how they solved a problem and why or how they chose a particular method. The use of CA strategies in mathematics lessons promotes critical thinking among all students because such a system facilitates the opportunity for teachers to challenge students to reflect on problems, think of an alternative approach to solving problems, and consider different scenarios where solutions to problems can be applied (Baumert et al., 2010). In addition, using CA strategies fosters a learning community where students can feel free to make mistakes, learn from their mistakes, and discuss alternative ways of solving problems in detail with their peers (OECD, 2014).Therefore, using CA as a mediator between MA and IM in the context of ML can shed light on how to reduce the negative effects of MA and boost IM for mathematical learning to improve performance.

Mathematical Literacy Performance

The Programme for International Student Assessment (PISA) is an international assessment measuring 15-year-old student reading, mathematics, and science literacy every three years (OECD, 2014). The OECD reports that over 75 countries conducted the 2012 assessment, collecting results from over half a million participating students. PISA administered the mathematical literacy test to all participants who completed their surveys. PISA divided the 2012 mathematical literacy assessment into two categories. The first category was mathematical content, which assessed change and relationships, space and shape, quantity and uncertainty, and data. The second category was the real-world context, which evaluated personal, societal, occupational, and scientific discoveries in solving problems.

PISA (von Davier et al., 2019) used student performance, the partial credit item-response theory (IRT) model, and the imputation methodology to create an achievement scale (5 plausible values) for each student. We used plausible values to rank the students. Within the OECD countries, the mean score for mathematics literacy was 494 points. Australia provided the data for the study. We conducted the assessment once again in 2012. This study used Australian data, as Australia has participated in all PISA assessments since 2000. Australia has developed better data collection systems compared to other countries that participate for the first time or only occasionally. Second, Australia's math ranking was closer to the standardized mean score of all countries that participated in PISA 2012 assessments. Therefore, the results of this study would be generalizable.

The Present Research

Researchers have conducted extensive research on MA and the motivation to learn mathematics. However, we further subdivide motivation to learn mathematics into various forms. This study focuses on IM to learn mathematics. As per reviewed literature, specific forms of motivation are relatively under-researched fields (Bol & Berry, 2005; Chang et al., 2016; Liu, Hau, & Zheng, 2018; Pitsia et al., 2017). Additionally, student CA is a relatively new variable for study in the context of mathematics lessons. In the 2012 assessment, PISA used CA as a construct. CA data first became available in 2014.

The present study has two objectives. First, the study will investigate the predictive strength of two independent variables (MA and IM to learn mathematics) within the context of their interaction with a dependent variable (ML). Second, this study will examine CA as a mediator variable between independent and dependent variables in mathematics lessons. Studying these constructs in an integrated and comprehensive model will permit simultaneous inspection of the construct relationships presented. In addition, the flexibility of the structural equation models (SEM) facilitates statistical analysis and tests required to answer hypothesized questions in this study.

The study hypothesizes that IM learning mathematics will be positively associated with CA in mathematics lessons and student performance in ML. It consequently postulates that MA will be negatively associated with CA in mathematics lessons and student performance in ML. Furthermore, it infers that CA in mathematics lessons will mediate between the study's independent and dependent variables. Finally, it predicts that the association among constructs will be invariable when student socioeconomic status and gender are considered.

Method

PISA has conducted assessments every three years since 2000. PISA evaluates students in mathematics, reading, and science. Each assessment cycle collects extensive data on one of the three subjects. In 2003 and 2012, PISA focused on mathematics. The study utilized data from 2012, as it gathered comprehensive information on every variable. We randomly selected a sample of 4,500 complete survey results from a total of 14,481 students surveyed. There were 7,075 (48.9%) females, 7,406 (51.1%) males, 8,679 (60%) high SES, and 5,431 (38%) low SES from the total number of students surveyed. About 371 (2%) responses were invalid in the SES column of the total number of students surveyed. The sample size for structural-equation modeling analysis depends on each study's number of variables and complexity (Iacobucci, 2010; Paiva & Reiter, 2015; Preacher & Merkle, 2012). We recommend a minimum of twenty or more records for each variable. Using this suggestion and comparing sample sizes from similar studies, we capped the sample size at 4,500, taking into account the number of variables and complexity.

We used four statements, such as "I am interested in the things I learn about in mathematics," to measure intrinsic motivation to learn mathematics (Cronbach's = 0.78). We used five statements to measure MA (e.g., "I often worry that it will be difficult for me in mathematics classes," Cronbach's = 0.85). We used nine statements, such as "The teacher presents problems in different contexts so that students know whether they have understood the concepts," to measure students' CA in mathematics lessons (Cronbach's = 0.87). Survey participants responded to each statement on a four-point Likert scale by choosing one of the following options: *strongly agree, agree, disagree, or strongly disagree*. We represented the student's gender and socioeconomic status (SES) as follows: female = 1, male = 2, low SES = 1, and high SES = 2. The sample consisted of 2,222 females (49%) and 2,278 males (51%), with low SES being represented by 1747 (38%) and high SES by 2753 (62%). We used five plausible values to assess performance in ML. PISA coded all items in each variable. We used a statistical package for the social sciences (SPSS) to describe the data. We used an analysis of moment structures (AMOS) to create structural equation models.

Linear correlations (Table 1) were used to assess multicollinearity among this study's variables. Correlation values between -0.7 and 0.7 indicate a lack of multicollinearity among predictor variables. It is recommended that absolute values should be more significant than 0.3 between each predictor and the dependent variable (Kargar et al., 2010b; Raykov, 2011; Whitley & Kite, 2013). Correlations among predictor variables were between -0.53 and 0.28. Correlation values between the predictor and dependent variables were between 0.15 and -0.39. All correlations were within the expected ranges.

Table 1. Summary of Descriptive Statistics and Intercorrelations for all Variables

		1	2	3	4
1	Intrinsic motivation to learn mathematics	1			
2	Mathematics Anxiety	-0.27**	1		
3	Cognitive activation in mathematics lessons	0.28**	-0.53**	1	
4	Performance in mathematics literacy	0.21**	-0.39**	0.15**	1
5	M	2.94	2.44	2.80	497.65
6	SD	0.67	0.64	0.63	92.37

Note. $N = 4500$, $^{**}p < 0.01$

We performed the following factor analysis on the data. First, the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was 0.925. Second, Bartlett's test of sphericity was $p < 0.001$. A KMO value greater than 0.7 and Bartlett's test of sphericity of $p < 0.001$ are acceptable (Iacobucci, 2010; Preacher & Merkle, 2012). All communality extractions were between 0.342 and 0.738. The total variance, cumulatively explained, was

65.359%. We extracted five factors with an eigenvalue greater than 1.

We used the average variance extracted (AVE) and composite reliability (CR) values to test convergent validity. Each variable had the following values (AVE/CR): IM to learn mathematics = 0.709/0.907, MA = 0.536/0.852, performance in ML = 0.879/0.973, and CA in mathematics lessons = 0.437/0.874. Convergent validity tests recommend an average variance extracted value equal to or greater than 0.5 and a composite reliability value equal to or greater than 0.7 on each variable (Carlson & Herdman, 2012; Duckworth & Kern, 2011; Raykov, 2011). However, according to Fornell and Larcker (1981), the construct's adequate convergent validity exists if AVE is less than 0.5 but CR is greater than 0.6. All composite reliability values were greater than 0.7. We conducted a discriminant validity test by comparing the discriminant values to their corresponding correlation values. We met the discriminant validity test requirement because all discriminant values exceeded their corresponding correlation values. Table 2 contains discriminant values for each latent variable and outlines correlation with other latent variables.

Table 2. Discriminant (in bold) and Correlation Values on Latent Variables

Latent Variables	Intrinsic Motivation	Math Anxiety	Cognitive Activation
Intrinsic Motivation	**0.841**		
Math Anxiety	-0.27	**0.732**	
Cognitive Activation	0.28	-0.53	**0.661**

Results

Hu and Bentler (1999) used the following indicators to test the model fitness of the study's data. The study included individuals with an SRMR of less than 0.08, a goodness of fit index (GFI) of at least 0.95, a Tucker-Lewis index (TLI) of at least 0.95, a comparative fit index (CFI) of at least 0.95, and an RMSEA of less than 0.06. This study also employed the maximum likelihood estimation method. The SEM model shows the fitness of the hypothesized model using all variables and the total sample size (N = 4500). Chi-square (920, N = 4500) = 6041, SRMR = 0.07, GFI = 0.96, TLI = 0.97, CFI = 0.98, RMSEA = 0.02, and RMSEA 90% confidence interval (0.020, 0.021) all indicate that the hypothesized model does indeed fit the data. IM to learn mathematics and CA in mathematics lessons (β = 0.31, SE = 0.02, p < 0.001) were statistically significant and positively related. IM to learn mathematics and performance in ML (β = 0.10, SE = 2.16, p < 0.001) were statistically significant and positively correlated.

CA in mathematics lessons and performance in ML (β = 0.05, SE = 2.54, p < 0.001) demonstrated statistically significant and positively related linkage. On the other hand, there was a statistically significant and negative link between MA and CA in math lessons (^{2} = -0.11, SE = 0.02, p < 0.001) and between MA and performance in ML (^{2} = -0.40, SE = 2.68, p < 0.001). CA in mathematics lessons partially mediated MA and performance in the context of ML variables (standardized indirect = - 0.01, p < 0.01). CA in mathematics lessons partially mediated IM to learn mathematics and performance in ML (standardized indirect = 0.02, p < 0.01).

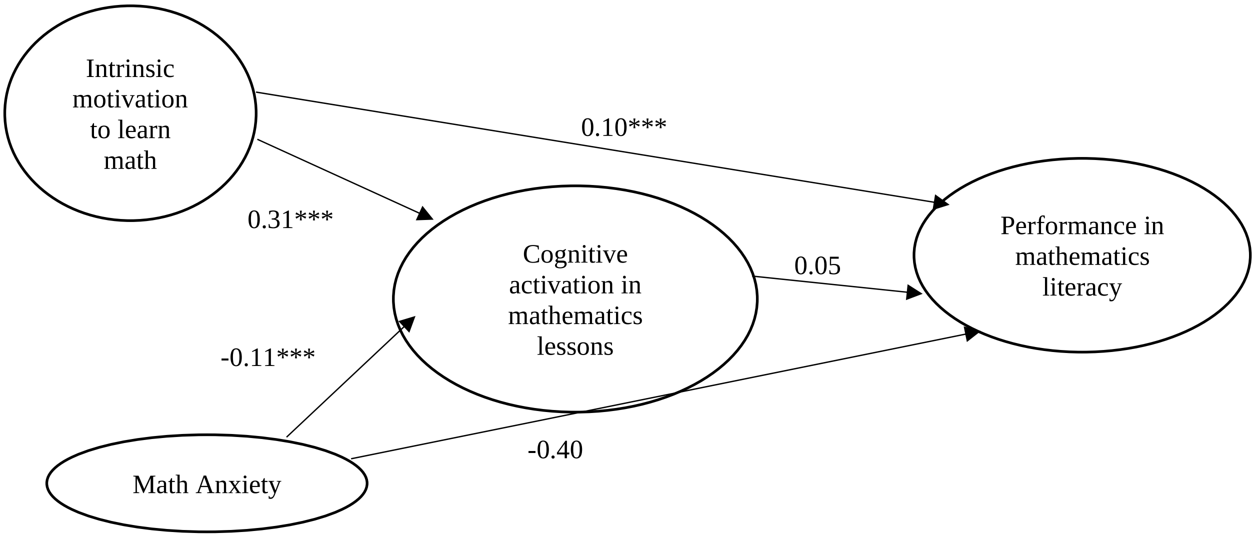

Figure 2. Standardized Estimates for Pathways between the Constructs for the Multi-Group Model. ***p < .001, **p < .01, *p < .05

The first multi-group model of female and male students in [Insert Figure 2 Here] involved the following model-fitness indices: Chi-square (920, *N* = 4500) = 6041, SRMR = 0.07, GFI = 0.96, TLI = 0.97, CFI = 0.97, RMSEA = 0.02, and RMSEA 90% confidence interval (0.020, 0.021). These indices indicate that the hypothesized model fits the data. Female students had the following results: IM to learn mathematics was statistically significant and positively associated with CA in mathematics lessons (β = 0.26, *SE* = 0.02, p < 0.001). MA and cognitive activation in mathematics lessons (β = - 0.13, *SE* = 0.03, p < 0.001) are statistically significant and negatively associated.

The association between MA and performance in ML is statistically significant and negative, with a value of -0.41, a standard error of 3.91, and a probability of 0.001. Both links were statistically significant and negatively associated. CA in mathematics lessons and performance in ML were significant and positively associated (β = 0.05, *SE* = 3.59, p = 0.022). IM to learn mathematics and performance in ML were statistically significant and positively associated (β = 0.09, *SE* = 2.96, p < 0.001). CA in mathematics lessons partially mediated MA and performance in the context of ML variables (standardized indirect = -0.01, p < 0.05). CA in mathematics lessons partially mediated IM to learn mathematics and performance in the context of ML (standardized indirect = 0.01, p < 0.05) for female students

. Male students had the following results: IM to learn mathematics was statistically significant and positively associated with CA in mathematics lessons (β = 0.35, *SE* = 0.02, p < 0.001). MA and CA in mathematics lessons (β = - 0.07, *SE* = 0.03, p < 0.001) correlate with MA and performance in the context of ML (β = - 0.38, *SE* = 3.99, p < 0.001). Both links were statistically significant and negatively associated. CA in mathematics lessons and performance in ML are positively associated (β = 0.05, *SE* = 3.58, p < 0.05). IM to learn mathematics and performance in ML were statistically significant and positively associated (β = 0.10, *SE* = 3.17, p < 0.001). CA in mathematics lessons partially mediated between MA and performance in the context of ML variables (standardized indirect = - 0.01, p < 0.05). CA in mathematics lessons partially mediated between IM to learn mathematics and performance in the context of ML (standardized indirect = 0.02, $p < 0.05$) for male students.

Figure 2

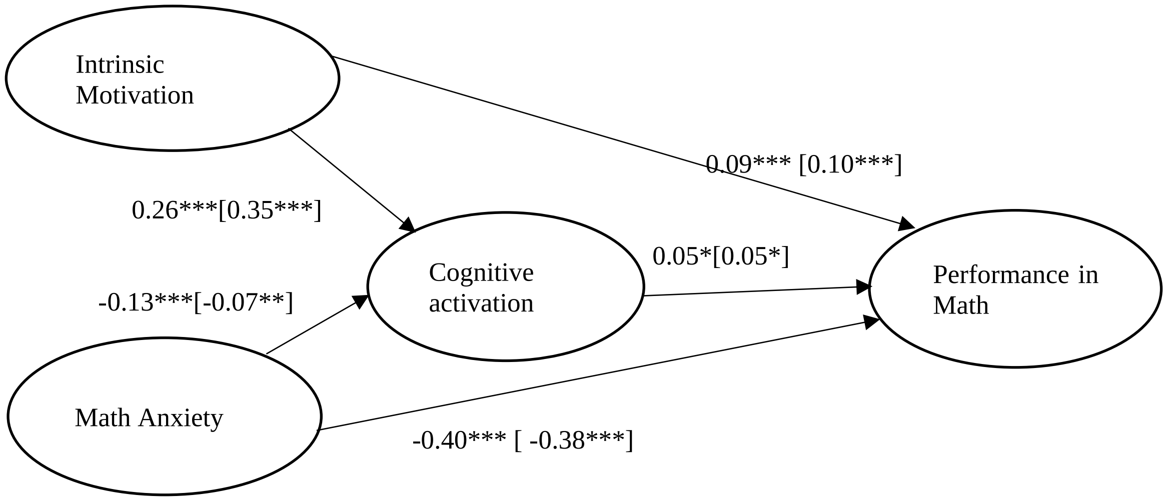

Figure 2. Standardized Estimates for Pathways between the Constructs for the Multi-Group Model (female vs. male; male in brackets). ***p < .001, **p < .01, *p < .05

The second multi-group model (low and high SES) students [Insert Figure 3 here] had the following model-fitness indices: Chi-square (920, N = 4500) = 6,041, SRMR = 0.07, GFI = 0.96, TLI = 0.97, CFI = 0.97, RMSEA = 0.02, and RMSEA 90% confidence interval (0.020, 0.021). These indices indicate that the hypothesized model fits the data. Low SES students had the following results: IM to learn mathematics was statistically significant and positively associated with CA in mathematics lessons ($\beta = 0.27$, $SE = 0.03$, $p < 0.001$). MA and CA in mathematics lessons ($\beta = -0.13$, $SE = 0.03$, $p < 0.05$) correlated with MA and performance in the context of ML ($\beta = -0.39$, $SE = 4.17$, $p < 0.001$).

Both links were statistically significant and negatively associated. CA in mathematics lessons and performance in ML were positively associated ($\beta = 0.01$, $SE = 3.90$, $p = 0.61$). Learning mathematics and performance in ML ($\beta = 0.13$, $SE = 3.44$, $p < 0.001$) are statistically significant and positively associated. CA in mathematics lessons did not mediate MA and performance in the context of ML variables (standardized indirect = 0.01, $p = 0.61$). CA in mathematics lessons did not mediate IM to learn mathematics and performance in ML (standardized indirect = 0.00, $p = 0.44$) for low SES students.

High SES students had the following results: IM to learn mathematics was statistically significant and positively associated with CA in mathematics lessons ($\beta = 0.36$, $SE = 0.02$, $p < 0.001$). MA and CA in mathematics lessons ($\beta = -0.05$, $SE = 0.02$, $p < 0.001$) correlated with MA and performance in mathematics literacy ($\beta = -0.38$, $SE = 3.19$, $p < 0.001$). Both links were statistically significant and negatively associated. CA in mathematics lessons and performance in ML were positively associated ($\beta = 0.05$, $SE = 3.11$, $p < 0.05$). IM to learn mathematics and performance in the context of ML were statistically significant and positively associated ($\beta = 0.11$, $SE = 2.56$, $p < 0.001$). CA in mathematics lessons was partially mediated between MA and performance in ML variables (standardized indirect = - 0.01, $p < 0.05$). CA in mathematics lessons partially mediated between IM to learn mathematics and performance in the context of ML (standardized indirect = 0.01, $p < 0.05$) for high SES students.

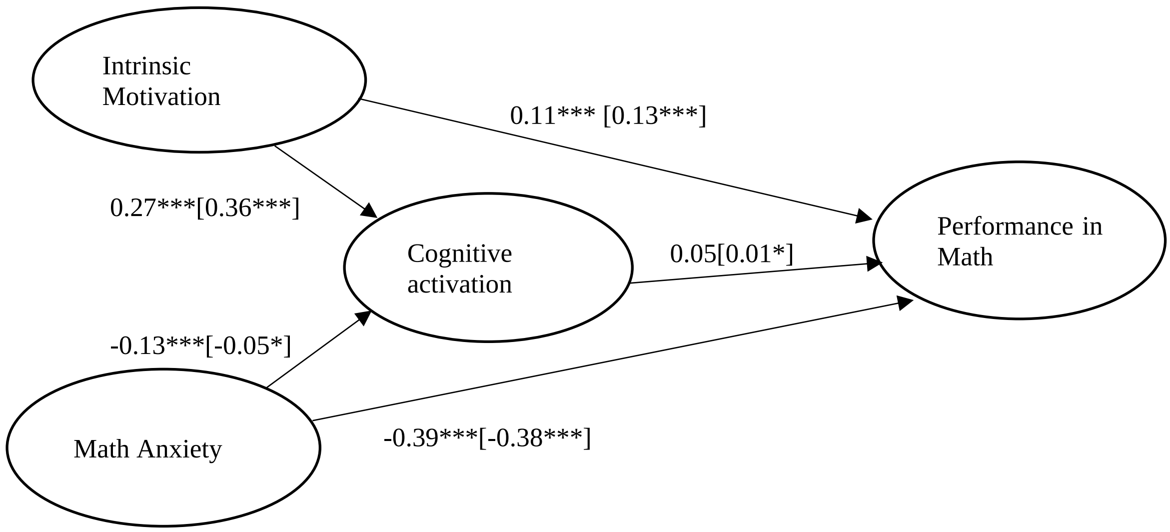

Figure 3. Standardized Estimates for Pathways between the Constructs for the Multi-Group Model (low SES vs. high SES; high SES in brackets). ***$p < .001$, **$p < .01$, *$p < .05$

Discussion

The present study examined the direct effects of IM on learning mathematics, CA in mathematics, and MA on performance in ML. Likewise, the indirect effects of IM to learn mathematics and MA on performance in ML mediated by CA in mathematics were tested. Second, MA will be negatively correlated with CA in mathematics lessons and students' performance in ML. Third, CA in mathematics lessons will mediate between independent variables (IM to learn mathematics and MA) and dependent variable (performance in ML).

The study found that IM to learn mathematics was statistically significant and positively associated with CA in mathematics lessons and performance in ML for the whole sample, gender, and SES. The findings suggest that IM learning mathematics (enjoying reading about mathematics or doing mathematics) facilitates CA in mathematics. Similarly, students who enjoy performing mathematics-related tasks may learn CA skills such as finding alternative ways to solve problems, thinking about problems for an extended time, and explaining their solutions, which, in turn, facilitates their CA in mathematics.

Second, intrinsically motivated students may practice more or challenge themselves with mathematics material beyond their classwork because they enjoy mathematics; therefore, their performance in ML improves. According to a 2014 OECD report, intrinsically motivated students tend to have a more positive attitude toward mathematics and enjoy performing arithmetic tasks. These factors are linked to improved mathematics performance, according to Cantley, Prendergast, and Schlindwein (2017).

MA was statistically significant and negatively associated with CA in mathematics lessons and performance in ML for the whole sample, as well as gender and SES. This would suggest that ML (feelings of helplessness and stress when dealing with mathematics problems) hinder students from asking for help, participating in class discussions or study groups, and understanding mathematical concepts, which, in turn, decreases their CA in mathematics lessons and performance in ML. Several other studies that looked at the links between ML, CA in math, and performance in ML agreed with this study's findings on MA (Chang & Beilock, 2016; Kargar et al., 2010b; Passolunghi, Caviola, De Agostini, Perin, & Mammarella, 2016; Stoet et al., 2016a; OECD, 2014).

The study's findings revealed that CA in mathematics lessons did not fully mediate between independent variables (IM to learn mathematics and MA) and the dependent variable (performance in ML). However, the study found weak ($\beta < 0.03$, $p < 0.05$) mediation for the whole sample and gender and SES. The OECD (2014) found a positive link between CA in mathematics lessons and improved ML performance. What could be the source of discrepancies? The role of CA in mathematics lessons in various studies may account for the discrepancies between the study's results and those cited in the literature review (Artemenko et al., 2015; Baumert et al., 2013; Förtsch et al., 2016; Weisseno & Landwehr, 2015). The study uses CA as a mediator in mathematics lessons, whereas the literature review cites other studies that show a linear relationship between CA and mathematics performance.

Implications for Educational Practice

Educators should equip themselves to assist students who encounter MA. Additionally, educators should encourage students to develop IM in order to learn mathematics. For example, educators can incorporate real-world application problems in their lesson plans to complement abstract mathematics concepts.

Working on real-world application problems may help students appreciate the relevance of mathematics concepts they learn. Our study results indicate that CA strategies are insufficient in addressing mathematics anxiety and the impact of IM on performance in machine learning. Therefore, we should limit the use of CA strategies in mathematics lessons to decrease MA and increase IM for mathematics learning.

Future researchers have several opportunities to investigate the study variables or add new variables to the models. For instance, conducting a bidirectional relationship study between the variables in the current study could provide valuable insights. Secondly, adding a new variable, such as the student's place of birth, will provide information for comparing the study variables’ effects on nonimmigrant and immigrant students. Third, converting the current models into multilevel models will foster a better understanding of the relationships among variables on different levels (i.e., within a school, school district, or state).

The present study has several limitations that future researchers may want to investigate. First, future researchers should seek a more effective mediator, as the CA in mathematics lessons variable did not effectively mediate between the independent and dependent variables in the current study, contrary to the hypothesis. Second, the study only sources its data from Australia, focusing on a narrow age range of 15 years old, without sampling data from other countries or a wider age range for comparison. Therefore, without including data from other counties, different age groups, and other factors that affect learning, the present study results cannot be applied in other countries without adjustments.

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