MOTIVATION, ANXIETY, AND WORK ETHIC AS MEDIATORS BETWEEN COGNITIVE-ACTIVATION INSTRUCTION AND MATHEMATICS AND SCIENCE PERFORMANCE

By

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DEDICATION PAGE

This dissertation is dedicated to my parents, Pastor Jonathan Mutua Mutuku (December 8, 1946 - June 27, 2017) and Mrs. Beatrice Ndumba Mutuku.

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

Figure **Page**

ABSTRACT

This study examined instrumental motivation to learn mathematics, mathematics anxiety, and mathematics work ethic as mediators of the relationship between cognitive activation instruction and mathematical and scientific literacy. Program for International Student Assessment (PISA) data were obtained on 4,500 students, 15-16 years old, from Australia. Structural equation modeling (SEM) was used to estimate mediational paths, and multi-group SEM was conducted to find out if these mediational paths were invariant across levels of socioeconomic status and gender. Results showed that the effect of cognitive activation in mathematics lessons on mathematics and science performance was significantly mediated by mathematics anxiety, instrumental motivation to learn mathematics, and mathematics work ethic. For the most part, gender and socioeconomic did not significantly moderator these mediational paths. The findings of this study converge with previous literature demonstrating benefits of cognitive activation instruction and expand this literature by explaining how cognitive activation instruction may influence math and science performance. Specifically, this study provides original correlational evidence that cognitive activation instruction helps to reduce anxiety and increase instrumental motivation, which in turn may increase work ethic and science and math performance. Mathematics work ethic, an understudied construct, should be examined in future motivational research and theory building, as it played an instrumental role in the models tested in this study. Practically, this study could help to inform educators about the potential benefits of using cognitive activation instruction in

the classroom and the important roles mathematics anxiety, instrumental motivation, and work ethic play in students' math and science performance.

I: INTRODUCTION

A common objective of school districts, states, and the federal governments is to increase students' competency in all subjects, but special emphasis is placed on ensuring a continuous growth in the number of students graduating with mathematics and science majors (Gastón, 2011). According to the Organization for Economic Co-operation and Development (OECD; 2004), the projected increase in science, technology, engineering, and mathematics (STEM) occupations is 14% between years 2010 and 2020. The expected percentage increases in STEM jobs within the same period are as follows: mathematics 16%; computer systems analysts 22%; computer software developers 32%; medical scientist 36%; and biomedical engineering 62%. Additionally, jobs in STEM fields are relatively well-paying, and they offer better career-advancement opportunities (Gastón, 2011). Despite the well-paid career prospects in STEM, many students enter college academically underprepared in general and specifically in STEM subjects (Reilly, Neumann, & Andrews, 2015; Siraj-Blatchford & Nah, 2014; Stoet, Bailey, Moore, & Geary, 2016).

Many colleges require students who score low on standardized admissions and placement tests to enroll in developmental education (or remedial) courses. These non-credit-bearing courses are designed to help students develop reading, writing, and mathematical skills; and their successful completion is typically a prerequisite to enrollment in specified credit-bearing college courses required for degree completion. Accordingly, students who enter college academically prepared for college work tend to graduate within a shorter time compared to their counterparts who need developmental education, or remedial, courses (Gastón, 2011). Gaston added that "college ready students" incur less tuition debt upon graduation. Also, compared to developmental education courses in writing and reading, a disproportionate number of first-year students enroll in developmental mathematics courses (Areepattamannil et al., 2016; Baumert et al., 2010; Gastón, 2011).

According to Dailey (2009), academic difficulties among college students often originate in high schools. Several factors contribute to students' graduation from high school without the necessary content mastery and the necessary study habits to succeed in postsecondary institutions. For example, poor work ethic develops before students enter college, partly because the culture of working has not been instilled in some students (Meriac, 2012; Meriac, Poling, & Woehr, 2009; Parkhurst, Fleisher, Skinner, Woehr, & Hawthorn-Embree, 2011). Likewise, students who are not motivated (self-driven) to excel academically in high school tend to struggle in college because they lack the resilience to overcome academic setbacks (Braver et al., 2014; Dailey, 2009; Pitsia, Biggart, & Karakolidis, 2017). Instrumentally motivated students are interested in learning mathematics because they appreciate the importance of mathematics in their future goals. Mathematics anxiety is another factor that tends to develop early in students' academic development and carries on through college. Studies have shown that students experience mathematics anxiety because they are inadequately prepared for the current course content which causes self-doubting in students' ability to handle assignments and tests (Burić, 2015; Kargar, Tarmizi, & Bayat, 2010; Lee, 2009; Maloney, Sattizahn, & Beilock, 2014). Accordingly, mathematics anxiety has been attributed to students' lack of self-confidence in dealing with numbers (Harari, Vukovic, & Bailey, 2013). Whenever measures are not taken to address mathematics anxiety among students earlier in their academic career (at middle and high school) the situation worsens as they progress (Dowker, Sarkar, & Looi, 2016). In sum, work ethic, instrumental motivation for learning mathematics and mathematics anxiety are three motivational and affective factors that students bring with them to college and can influence their performance on placement tests and in developmental education mathematics courses. Cognitive-activation instruction is one approach that has the potential to improve these motivational and affective factors during high school and college.

Cognitive-activation instructional strategies teach students how to approach problems from different perspectives by scrutinizing the approach presented to them (Cantley, Prendergast, & Schlindwein, 2017)**.** The use of cognitive-activation instructional strategies, for instance, asking follow-up questions to ensure students' understanding and allowing students to explore alternative methods of solving mathematics and science problems, is a promising approach which addresses various learning challenges experienced by students (Braver et al., 2014; Cantley et al., 2017; Maloney et al., 2014). In general, researchers have found that cognitive-activation strategies help students improve their motivation for learning mathematics and performance (Ashcraft, 2002; Braver et al., 2014; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016). Previous studies have shown positive and statistically significant relationships between cognitive-activation instruction and students' performance in mathematics and sciences (Baumert et al., 2010; Braver et al., 2014; Cantley et al., 2017). Cognitive-activation instruction has also been found to increase students' self-confidence in dealing with mathematics and science problems (Artemenko, Daroczy, & Nuerk, 2015; Halpern et al., 2007; Maloney et al., 2014). However, the relation between cognitive-activation in mathematics lessons and mathematics anxiety is inconclusive (OECD, 2014). After conducting an extensive literature review, I found no studies that had examined students' motivation to learn mathematics, anxiety, and work ethic as mediators between cognitive-activation instruction and their mathematical and scientific literacy.

Purpose Statement

The purpose of this study is to propose and test a path model that could help explain the mechanisms through which cognitive activation in mathematics lessons influences students' performance in mathematical literacy and scientific literacy. More specifically, I am proposing that instrumental motivation to learn mathematics, mathematics anxiety, and mathematics work ethic mediated the relationship between cognitive-activation instruction in mathematics lessons and students' PISA test scores in mathematical literacy and scientific literacy. Also, I intend to investigate students' gender and socioeconomic status as possible moderators of this path model because gender and socioeconomic status have been found to have strong influences on students' mathematics performance and responses to setbacks (Stoet et al., 2016).

This study is necessary, given the positive associations among cognitive activation in mathematics and instrumental motivation to learn mathematics with students' performance in mathematical literacy and scientific literacy (Areepattamannil, 2014; Chang et al., 2016; Schofield, Junker, Taylor, & Black, 2015). Likewise, numerous studies have found that mathematics anxiety is negatively related to students' performance in mathematical literacy and scientific literacy (Artemenko et al., 2015;

Ashcraft, 2002; Novak & Tassell, 2017). However, based on reviewed studies, none have investigated the impact of mathematics work ethic on students' performance in mathematical literacy and scientific literacy as an independent variable or together with the other constructs examined in this study.

The Significance of the Study

Motivational and affective factors, such as instrumental motivation, mathematics work ethics, and mathematics anxiety play significant roles in students' learning, yet few studies have examined the relationships among them and the influences they have on students' performance (OECD, 2014). This study quantified the relationships among four motivational and affective factors and their influences on students' performance in mathematical literacy and scientific literacy. Also, the use of structural equation model (SEM) method for data analysis facilitated comparison of the predictive strength of the study variables. Mathematics work ethic is a relatively new instrument. The Programme for International Student Assessment (PISA) developed the instrument and used it in PISA, 2012 assessment for the first time (OECD). This study examined the mediational role of the mathematics work ethic variable.

Cognitive and non-cogitative skills are complementary to each other (Bishop Smith et al., 2012; Pitsia, Biggart, & Karakolidis, 2016). Students who utilize these skills tend to excel in standardized assessments more than their counterparts who disregard the use of these skills in their studies or have not developed such skills (Burić, 2015; Cantley et al., 2017; Förtsch, Werner, von Kotzebue, & Neuhaus, 2016). Informally, the importance of motivational and affective factors in improving students' success is widely acknowledged by educators, parents and other stakeholders in the education sector

(Caughy, DiPietro, & Strobino, 1994; Meriac, 2012; Middleton & Spanias, 1999). However, research on the influence of motivational and affective factors is scarce, and the results of available studies lack vigorous evidence because the majority of these studies used bivariate (two variables) data analysis method. For example, finding the relation between students' motivation to learn mathematics and their performance in mathematics, while ignoring other factors associated with this relation like students' gender and socioeconomic status. For instance, several studies have found a significant positive relationship between students' motivation to learn mathematics and their performance in mathematics (Braver et al., 2014; Garon-Carrier et al., 2016; Middleton & Spanias, 1999). Likewise, mathematics anxiety (fear of failure) is negatively associated with students' performance in mathematics (Kargar et al., 2010; Maloney et al., 2014; Novak & Tassell, 2017).

This study contributed towards improving the scope of the current literature by examining the foretelling influences of the study variables and the interrelation among the study variables when examined simultaneously in an all-inclusive model using the SEM. Furthermore, this study incorporates a relatively new variable (mathematics work ethic) which has scarcely featured in previous studies compared to the other variables (instrumental motivation to learn math, mathematics anxiety, and cognitive activation in mathematics lessons) and students' background information (gender and socioeconomic status) are used in this study. The mathematics work ethic instrument designed and was used for the first time in the PISA, 2012 assessments (OECD, 2014).

Why Programme for International Student Assessment (PISA)?

Programme for International Student Assessment (PISA) assess the performance of 15 years old students in the Organisation for Economic Co-operation and Development (OECD) countries and non-member countries in mathematics, science, and reading. The majority of students within OECD and non-member countries which participate in the assessment are 15 years old, and they are high school juniors or seniors. Furthermore, high graduation marks the end of compulsory education as well as prepares students for postsecondary education, vocational training or joining the labor market in many OECD member countries. PISA “aim is to provide comparable data intending to enabling countries to improve their education policies and outcomes" (OECD 2000, p.17).

The assessment is conducted triennially since the year 2000. In each assessment cycle, PISA focus on one of the three subjects. For example, in the year 2000 PISA assessment focused on reading literacy, in 2003 the focus was on mathematics literacy and in 2006 the PISA assessment focused on scientific literacy. Whenever a subject is being focused on, students respond to more questions related to the subject or new test questions related to the subject are introduced, and more data related to the subject under focus is collect. Additionally, students are also assessed in the other two subjects in each testing cycle.

Since the year 2000 PISA has accumulated huge datasets which are accessible to the public free of charge. The availability of large dataset together with increased analytical capabilities has accelerated research in correlational studies (Halpern et al., 2007; Harari et al., 2013; Reilly et al., 2015; Rosenthal, London, Levy, Lobel, & Herrera-

Alcazar, 2011). Therefore, enabling researcher test more hypotheses, discover new patterns among variables, and correct or challenge the previous conclusion.

PISA dataset (Australia) was uniquely suited for this study because over 14,000 students participated in the assessment in the year 2012. The large sample size is sufficient for the data analysis technique used in this study (structural equation modeling). Also, the data was availed at no cost, and it included variables examined in this study. PISA assessment report provided comprehensive information on how the assessment was constructed, validated, administered, and the data collection process before, during and after the assessment. Likewise, the sampling process of participating countries, schools and students was also documented.

Why Australia?

Several reasons made the Australian students' data ideal for this study. First, Australia data collection was extensive, because Australian students were assessed on an optional section of the PISA, 2012 assessment. Parental data (income, house possessions and education level) survey was optional in PISA, 2012 assessment cycle. Many countries opted out of the optional sections of the assessment. Parental information was used to construct the socioeconomic variable. Second, the data collection method used in Australia ensured equal representation of the diverse students' population. For example, data were collected from students in urban and rural school, students in high and low socioeconomic schools and among Australian born and migrant students. The diversity in the data increased the likelihood of the study's findings being duplicated. Third, PISA 2012, minimal sample size per country was 4,500 students. However, over 14,200 students participated in PISA, 2012 in Australia. A large data set is needed for data-intensive analysis methods like the structural equation method (SEM) which was used in this study. Also, Australian dataset is publicly available and easy to manipulate. Fourth, in Australia, students are instructed in English, the official PISA 2012 assessment was written in English and French. Therefore, no meaning was lost in translation, and no additional costs were incurred in translation. Fifth, Australia has participated in international assessments like the Trends in International Mathematics and Science Study (TIMSS) and PISA assessments since 2000. Consequently, there is a higher possibility of hiring staff who are familiar with or experienced in PISA assessment procedures compared to countries which were participating for the first time. Having experienced staff administer the assessment, code and collect performance data has the potential of minimizing errors and increases the accuracy of the data.

Statement of the Problem

Australian students have participated in PISA since its inception in 2000 (OECD, 2014). However, their performance in mathematical literacy has been on a downward trend since 2000. Australia rankings in mathematical literacy among the OECD member nations in PISA are 5/32 in 2000, 8/29 in 2003, 9/30 in 2006, and 9/34 in 2009 and 12/34 in 2012. (OECD). Australian students' performance in scientific literacy is slightly better than their performance in mathematical literacy (McConney & Perry, 2010 & Thomas, Muchatuta, & Wood, 2009). Australia rankings in scientific literacy among the OECD member nations in PISA assessments are 7/32 in 2000, 4/29 in 2003, 5/30 in 2006, and 7/34 in 2009 and 10/34 in 2012 (OECD). Although Australia has been on the top 10 in scientific literacy since the inception of PISA, from 2006, Australia's performance in scientific literacy has taken a downward trajectory (Thomas et al., 2009).

Several reasons have been cited for Australia's declining performance in mathematics and science within and outside the country. According to (McConney & Perry, 2010; Thomas, 2011; Thomas et al., 2009) there is an acute shortage of qualified teachers for mathematics and science at middle school and high school. The deficit is notably worse in the rural areas and among minority communities. The shortage has persisted despite vigorous efforts by the states and federal governments to encourage students to major in Science, Technology, Engineering and Mathematics (STEM) (Hunter, 2017; van Kraayenoord & Elkins, 2013). Few students who graduate with STEM degrees are offered better career opportunities elsewhere, and those who pursue teaching are not motivated because they view teaching as a "stepping stone" to other careers which reward their skill at a better rate than the teaching profession (van Kraayenoord & Elkins, 2013). "Approximately 40% of Australian Years 7–10 classes (middle and high school) are taught by an unqualified mathematics teacher" (Prescott, 2014, p.7).

Closely associated with mathematics teacher shortage is the number of students enrolled in Calculus-based mathematics in high school. Students feel inadequate to pursue Calculus-based mathematics partly because they are unprepared or they were not adequately challenged in prerequisite courses (Hunter, 2017; McConney & Perry, 2010; Prescott, 2014). Without Calculus-based mathematics, it is almost impossible for students to pursue majors in STEM (Prescott, 2014). "In 2006 only 64% of high schools offered advanced mathematics at Year 12 (high school). Low socio-economic, rural and remote areas are faring the worst" (Thomas, 2011,p.19). Therefore, the challenges of teacher shortage and low students enrolment is STEM are impeding Australia efforts towards improving her performance in mathematics and science.

Australia ranking in mathematics and science performance on international tests could be worse than reported at the moment (Thomson, De Bortoli, & Buckley, 2012; Turner & Adams, 2007; van Kraayenoord & Elkins, 2013). According to Jerrim, (2015), the increase of students from East Asia countries (Hong Kong, South Korea, and Singapore) in Australian schools has "inflated" Australia performance in the international test. Jerrim found that mathematics and science scores of students from East Asia countries in Australian schools were similar to mathematics and science scores of the counterparts in East Asia countries. These scores were considered outliers when compared to scores of students born in Australia (Jerrim). Consequently, there is an urgent need to increase students' enrollment and graduation rates in mathematics and science in Australia.

Research Questions and Hypotheses

The premise of this study is that cognitive activation in mathematics influences students' attitudes towards mathematics and science. First, cognitive activation tasks in a mathematics class motivate students to pursue the subject or discourage students from studying mathematics. Second, mathematics work ethics mediate students' performance. For example, motivated and anxious students who have developed productive mathematics work ethics are likely to improve their performance in mathematics and science (Areepattamannil et al., 2016; Parkhurst et al., 2011). Likewise, the performance of motivated and anxious students who practice unproductive mathematics work ethics is expected to decline.

Therefore, this study answered the following questions:

Research Question 1.

Do students' instrumental motivation, anxiety, and work ethic for mathematics mediate relationships between cognitive-activation instruction and students' PISA test scores in mathematical literacy and scientific literacy?

Hypothesis 1a. Cognitive-activation instruction will positively predict students' instrumental motivation for mathematics which will positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Hypothesis 1b. Cognitive-activation instruction will negatively predict students' anxiety for mathematics which will negatively predict students' PISA tests scores in mathematics and science.

Hypothesis 1c. Cognitive-activation instruction will positively predict students' instrumental motivation for mathematics which will positively predict students' mathematics work ethic which will, in turn, positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Hypothesis 1d. Cognitive-activation instruction will negatively predict students' anxiety for mathematics which will negatively predict students' mathematics work ethic which will, in turn, positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Rationale

Cognitive-activation instruction in mathematics has been found to motivate students to study mathematics, increasing their likelihood of excelling in mathematics and science (Areepattamannil, 2014). Likewise, cognitive-activation instruction in mathematics is likely to increase students’ understanding of mathematics, helping them to gain self-confidence and reducing their mathematics anxiety. Appropriate cognitive-activation instruction in mathematics has been found to inspire students’ self-confidence in their own ability to excel in mathematics and science, the desire to explore new concepts before they are covered in class, and resilience against learning setbacks (Baumert et al., 2010; Cantley et al., 2017; Förtsch, Werner, Dorfner, et al., 2016).

Whenever students understand the core concepts behind how to solve a mathematical problem or how to apply a formula correctly, they are more empowered to deal with variations in the applications of concepts than students who memorize formulas without comprehension (Bishop Smith et al., 2012; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016; Maloney et al., 2014). Cognitive-activation tasks should be appropriate for the targeted students (Burić, 2015; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016). For example, if talented students are assigned easy cognitive tasks, they become bored. Likewise, when struggling students are challenged with advanced cognitive tasks, they become discouraged and disengaged and are likely to become anxious (Ashcraft, 2002; Braver et al., 2014; Cantley et al., 2017). On the contrary, appropriate cognitive activation in mathematics motivates and empowers students to peruse mathematics (Areepattamannil, 2014; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016).

Also, mathematics work ethics are hypothesized to be significantly positively related to students' performance in mathematics and science. Work ethics are more closely related to students' beliefs and attitudes towards the rewards of work than to their intelligence (Meriac, 2012; Meriac, Thomas, & Milunski, 2015). Intelligent and motivated students who do not appreciate the benefits of work are easily distracted from their goals because they lack the self-reliance required to overcome academic setbacks (Meriac et al., 2009). Additionally, students who lack work ethics tend to value leisure and have poor time management skills. All students (from high- to low-performing student) tend to benefit from the continuous improvement of their mathematics work ethics (Areepattamannil et al., 2016).

Mathematics work ethics inspire students to believe that hard work is an essential prerequisite to excelling academically in general and in mathematics and science in particular. Work ethics can guide students to find a balance between productive work and leisure time and helps them to emphasize the importance of sound time management (Meriac et al., 2009; Parkhurst et al., 2011; Rosenthal et al., 2011). Therefore, mathematics work ethics are expected to be positively related to student performance. Besides, students' motivation and anxiety are expected to predict students' work ethics. When students have strong reasons for learning mathematics, it should lead them to develop a stronger work ethic. When students have high anxiety, it should lead them to have a weaker work ethic (Areepattamannil et al., 2016; Park & Hill, 2016; Rosenthal et al., 2011).

Research Question 2.

Does students' gender or parental income moderate any of the mediational paths proposed under Research Question1?

Hypothesis

Hypothesis 2a. One or more of the mediational paths proposed under research Question 1 will be moderated by gender.

Hypothesis 2b. One or more of the mediational paths proposed under research Question 1 will be moderated by students' family income.

Rationale

Although the gender gap in students' mathematics and science performance is gradually closing, girls self-reported low ratings of resilience after experiencing a setback such as failing a test in mathematics, therefore, developing negative attitudes and higher levels of mathematics and science anxiety than boys in numerous surveys (Else-Quest, Hyde, & Linn, 2010; Kargar et al., 2010; Pitsia et al., 2016). Girls self-reported negatively on a wide variety of motivational and affective factors in the PISA survey at a higher rate than boys (PISA, 2013). According to Pitsia, Biggart, and Karakolidis (2017), whenever remedial measures are not taken to correct students' negative self-beliefs in their ability to master mathematics, students tend to perceive mathematics as a "difficult" subject where their efforts are not rewarded. "Once these perceptions are established, it acts as determinants of action and further development at the cognitive, social, and emotional levels and, consequently, of academic achievement" (Karakolidis, Pitsia, & Emvalotis, 2016a, p.41). Given the history of documented differences between males and females in mathematics, it seems possible that the proposed mediational paths from cognitive-activation instruction through motivation, anxiety, and work ethic to performance in mathematical literacy and scientific literacy might vary in strength and/or direction for males and females.

The learning experiences of students from low socioeconomic status families are different from their counterparts from high socioeconomic status families (Merola, 2005). For example, students from low socioeconomic status families start school with a low mastery of vocabulary, counting ability, and more moderate ability in the manipulation of numbers (OECD, 2014). Additionally, these students have been found to lack the necessary resources, role models, and enabling learning environment to catch up with their counterparts from high-income families (Bishop Smith et al., 2012; Burić, 2015). Therefore, their academic experiences are marked by numerous challenges. Efforts geared toward addressing these challenges experienced by students from low socioeconomic status families divert valuable instruction time and scarce learning resources (Halpern et al., 2007; Karakolidis, Pitsia, & Emvalotis, 2016b; Kim, Ham, & Paine, 2011; Pitsia et al., 2017). Given these additional challenges faced by students who come from lower-income families, it is plausible that the proposed mediational paths from cognitive-activation instruction through instrumental motivation, anxiety, and work ethic to performance in mathematical literacy and scientific literacy might vary in strength and direction for students with higher and lower family income levels.

Definition of Terms

Cognitive activation in mathematics lessons (referred to henceforth as cognitive-activation instruction) is a teaching strategy that “ignites” students’ thinking, questioning, summering, and predicting skills by encouraging students to think of alternative ways of solving the same problem (Cantley et al., 2017).

Instrumental motivation to learn mathematics “is the drive to learn mathematics because students perceive it as useful to them and their future studies and careers.” (OECD 2014, p.21).

Mathematics anxiety is defined as “a feeling of tension, nervousness and worrying about failure" that interferes with the manipulation of numbers and the solving of mathematical problems in . . . ordinary life and academic situations" (Ashcraft, 2002, p.7).

Mathematics work ethics is the principle that hard work is intrinsically virtuous or worthy of reward (Park & Hill, 2016).

Plausible values are "multiple imputations of the unobservable latent achievement for each student" (Wu, 2005, p.49). This term is relevant to this study because PISA assessments incorporate planned missing data design. Therefore, plausible values were used to determine students' performance in mathematics and science.

Literacy: "The term *literacy* is attached to each domain (mathematics, science & reading) to reflect the focus on these broader skills and as a concept, it is used in a much broader sense than simply being able to read and write" (OECD, 2014, p.87).

Mathematical literacy: "is an individual's capacity to identify and understand the role that mathematics plays in the world, to make well-founded judgments, and to engage in mathematics in ways that meet the needs of that individual's current and future life as a constructive, concerned and reflective citizen" (OECD 1999, p.90).

Scientific literacy: "means that a person can ask, find, or determine answers to questions derived from curiosity about everyday experiences. It means that a person can describe, explain, and predict natural phenomena" (Dani, 2009, p.11).

Missing Data: Missing data mean that one or more observation(s) expected in a dataset has a null value (Gemici, Bednarz, & Lim, 2014).

Mediator: is a third (or more) variable(s) through which represents a temporal step between the independent and dependent variables. (Iacobucci, 2010; Suhr, 2006).

A moderator is a qualitative variable like gender or socioeconomic status or quantitative variable like a person's income bracket. If the moderator variable is statistically significant, it can weaken or strengthen the effect between an independent and a dependent (Iacobucci, 2010; Suhr, 2006).

Structural Equation Model (SEM): is a multivariate statistical analysis technique which combinations of factor analysis and multiple regression analysis. It is used to analysis relationship between measured variables and latent constructs (Brandmaier, von Oertzen, Mcardle, & Lindenberger, 2013; Levy, 2011; Preacher & Merkle, 2012).

Multi-Group Structural Equation Model: is used to measure invariance in group comparison. The focus is on assessing the distinct features of each group and variation across groups. Groups may be countries, industries, gender, and education, extra (Brandmaier, von Oertzen, Mcardle, & Lindenberger, 2013 & Levy, 2011).

Path Analysis: is a subset of structural equation model (SEM). Path analysis comprises only observed variables and has restrictive assumptions than SEM. Path analysis assumes that all variables are measured without error. SEM uses latent variables to account for measurement error (Brandmaier et al., 2013).

General Linear Modeling: “is a generalization of multiple linear regression models to the case of more than one dependent variable” (Graham, 2007).

Latent constructs: are variables that are not directly observed but are rather inferred from other variables that are observed (Suhr, 2006).

Chapter I Summary

In this chapter, the study introduction was explained. For example, background information on the importance of increasing mathematics and science graduate and the need to adequately prepare high school students for STEM majors in postsecondary institutions. Second, the purpose and significance of this study and the gaps in the current literature were also discussed. Third, Key terms used throughout the proposal were defined and briefly explained. The source of data used in the study and the reason for using data from this source (PISA and Australia) were clarified. Finally, the study questions and hypotheses and rationale were expounded.

II: REVIEW OF THE LITERATURE

Overview

In this section, the literature about the control-value theory of achievement emotions and the constructs which tend to contribute to the success or failure of students in mathematics and science were reviewed. Additionally, the influence of mathematics teachers (supportive relationship), the challenges that teachers and students experience in the absence of a supportive relationship, and the importance of cognitive activation in mathematics lessons to students was explained. Second, attributes associated with students' success in mathematics such as interest in, instrumental motivation to learn mathematics and attributes associated with students' failure in mathematics like mathematics anxiety were explored. Third, a comparison between students' performance in mathematics based on gender and family income (wealth) were examined. Finally, the significance of students' mathematics work ethic towards their performance in mathematics and science was being explained.

Theoretical Framework: Control-Value Theory

The review begins with literature that seeks to understand why the control-value theory of achievement emotions is a useful framework for understanding the impact of cognitive activation in mathematics among students and how the control-value theory can be applied to help students who are instrumentally motivated to learn mathematics and students who exhibit mathematics anxiety. This study’s findings on the influence of cognitive activation in mathematics lessons on students’ instrumental motivation to learn mathematics and students’ mathematics anxiety were cross-referenced to explain students’ performance in mathematics and science from the control-value theory of achievement emotions perspective. Finally, the mediation role of instrumental motivation for learning mathematics, mathematics anxiety, and mathematics work ethics variables were presented and discussed.

The control-value theory of achievement emotions provides an integrated framework for understanding emotions in achievement settings (Pekrun, 2006). Control appraisals define an individual's being in charge, or their ability to regulate actions and outcomes. Likewise, value appraisals define the importance of activities and their outcomes. Students' understanding of course contents or activities triggers a feeling of being in control. For example, when students use different methods to solve a mathematical problem, they are assumed to be in control of the activity compared to their counterparts, who may be confused or unsure of the best method to use for solving the problem. Likewise, when students value an activity and anticipate rewards from the activity their commitment to the activity tends to be higher.

According to CVTAE (2006), students' emotions in a learning and achievement setting are influenced by several factors. First, the environmental factors which influence students' emotions are the instruction (cognitive quality and task demands), value induction, autonomy support, goal structures, expectations, and achievement (feedback and consequences). Artino, Holmboe, and Durning (2012) characterized instruction under the environment factor as engaging learning activities in the classroom and the ability of the course instructor to match learning tasks with students' competency levels.

Furthermore, Artino, Holmboe, and Durning found that when lessons are engaging, students' understanding of the course content is enhanced. Likewise, students' participation in classroom activities like group discussions or volunteering to explain their work to the whole class was much better compared to their studies control group.

Artino, Holmboe, and Durning studies compared students' levels of engagement to their performance on a variety of learning tasks and found that there was a positive relationship between students' engagement and their performance. Additionally, instructors' ability to foster a conducive learning environment in which students from different backgrounds and capabilities feel appreciated is vital to motivating students (Pekrun, 2006). For example, instructors should show enthusiasm, provide encouraging and timely feedback, support autonomy and self-regulated learning, and meet students' relatedness needs. According to Pekrun (2006), these positive environmental factors of CVTAE help students to gain control over and better value the subject content. Pekrun also observed that high control triggers joy among students and lack of control triggers hopelessness.

The control-value theory of achievement emotions (CVTAE) is appropriate for this study because it purports that environmental factors influence students' control and value appraisals which in turn influence students' achievement emotions. Achievement emotions influence students' motivation and learning which in turn affects their academic achievement. In this study, I am interested in a subset of related variables that align with the paths proposed in control-value theory. Specifically, I am interested in how cognitive-activation instruction (an environmental variable) influences students' instrumental motivation for mathematics (a type of value appraisal) and mathematics anxiety (an achievement emotion) which in turn influences students' PISA test scores in mathematics and science (an achievement variable). Instrumental motivation refers to students' appraisals to the extent to which learning mathematics is valuable because it will help them attain their future goals. Conceptually, mathematics work ethic aligns with students' motivation for learning within control-value theory because it concerns students' diligence, perseverance, and willingness to exert effort towards learning mathematics. Given the placement of the study variables within the control-value theory, my proposed model treats instrumental motivation and mathematics anxiety variables as antecedents to mathematics work ethics variables. The results of this study expound on the control-value theory of achievement emotions (CVTAE) by quantifying the influence of this study's variables on students' achievement on PISA. This study utilized the quantitive capabilities of Statistical Package for the Social Sciences (SPSS) and Analysis of a Moment Structures (AMOS) to explain the quantitative relations between cognitive activation in mathematics lessons, instrumental motivation to study mathematics, mathematics anxiety, mathematics work ethics, and students' performance in mathematics and science. Additionally, this study includes an analysis of gender and socioeconomic status variables which were not explicitly discussed in the CVTAE. In the following sections, I reviewed the literature on each variable in this study.

Cognitive Activation in Mathematics

Baumert et al., (2010) defined cognitive activation as teaching strategies that "ignite" thinking, questioning, summering, and predicting skills by, in essence, cognitive activation skills, instead of the memorization of a formula, encourages conceptual understanding of the course content among students (Förtsch, Werner, von Kotzebue, et al., 2016). There are three components of high-quality instruction that foster cognitive activation in a mathematics lesson (Baumert et al., 2010; Förtsch, Werner, von Kotzebue, et al., 2016; Weisseno & Landwehr, 2015). These components are “cognitively challenging and well-structured learning opportunities, learning support through monitoring of the learning process, individual feedback, and adaptive instruction; and efficient classroom and time management” (Baumert et al., 2010).

First, in cognitively-challenging and well-structured learning classes, teachers create opportunities for students to explore different ways of solving mathematics problems. They are required to work in collaboration with each other to share ideas, explain their work to their classmates, and explore alternative ways of solving problems or confirming their answers. In a cognitively challenging classroom, teachers guide students’ discussions, explain new concepts, and clarify misunderstandings among students. For instance, teachers utilize the following skills to enhance students’ engagement and their content understanding:

> Teachers present problems in different contexts so that students know whether they have understood the concepts, teachers’ present problems that require students to apply what they have learned to new contexts, teachers present problems in different contexts so that students know whether they have understood the concepts, and teachers ask us to decide on our procedures for solving complex problems (OECD, 2014, p. 64).

Moreover, teachers challenge students to think of hypothetical scenarios that are identical to the current discussion topic(s), provoke them with contradictory ideas or interpretations, and encourage their discourse (Förtsch, Werner, von Kotzebue, et al., 2016). For example, in a cognitively challenging lesson, students answer these types of questions "Why did you choose that method or formula to solve this problem?" "Might there be an alternative method or formula for solving this question?," and "How do I check my solution?" (OECD, 2014, p. 13).

Teachers' content knowledge and pedagogical content knowledge are vital for their successful implementation of cognitively-challenging and well-structured classes (Chauvot, 2008; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016; Förtsch, Werner, von Kotzebue, & Neuhaus, 2016). Teachers utilize content knowledge to select academically challenging tasks for students after reviewing their competency levels. According to Cantley, Prendergast, and Schlindwein (2017), easy tasks may be boring for students, leading to disengagement from the learning process, causing an interruption in class. Likewise, challenging tasks may frustrate students or discourage them from trying, consequently demoralizing the "discovering spirit" among students. Pedagogical content knowledge helps teachers to deliver subject content or adjust their lesson plans to suit the understanding of their students. When teachers are explaining new concepts to quick learners, they may move at a relatively faster compared to when they are teaching average or struggling students.

Second, learning support through the monitoring of student's learning process, individual feedback, and adaptive instruction are essential aspects of cognitive activation. At some point as they construct knowledge, students are likely to encounter obstacles (Förtsch, Werner, Dorfner, et al., 2016; Förtsch, Werner, von Kotzebue, et al., 2016). Through the continuous monitoring of students' learning progress, experienced teachers are likely to anticipate challenging concepts and avail more timely assistance to students. Alternatively, when students encounter difficulties beyond the anticipated content sections, they should be encouraged to seek help from the teacher or qualified tutors.

Timely assistance to students motivates them to continue working (Braver et al., 2014). Also, students gain control and autonomy (self-belief) in their mathematics skills (Weisseno & Landwehr, 2015).

Supportive learning environments after school or during long holidays (summer), including tutoring or at home and the availability of role models (parents and sibling pursuing careers or majors in mathematics and sciences), were positively associated with improved students' attitudes towards mathematics (Pitsia et al., 2016). Quinn (2014) found that students who attended summer classes performed significantly better than students who did not. Quinn also found that students' racial orientation was not related to their performance. Also, holding positive attitudes towards a subject tends to motivate students to study and ignite their curiosity about the subject (Pitsia et al., 2016).

Further, teachers' feedback and adaptive instructions encourage inclusivity and student-teacher relatedness (Cheon, Reeve, & Song, 2016). In the recent past, the student population has become gradually more diverse regarding students' competency levels in mathematics, their nationalities, and their self-beliefs (Pitsia et al., 2016). Student-teacher relatedness enables teachers to accommodate different learning styles, improves communication between students and teachers, and reduces interruptions in class, thus increasing time spent on instruction and student participation in assigned tasks. A conducive learning environment in the classroom is likely to increase students' cognitive skills (Cantley et al., 2017).

Third, efficient classroom and time management skills are crucial because cognitively challenging classrooms are relatively "busy" and "active," with students assigned and reassigned to different groups. Likewise, students in cognitively challenging classrooms become passionate or "charged" as they defend or explain their solutions. For this reason, teachers play a critical role in ensuring order in the classroom. In maintaining order and a suitable learning environment for all students, teachers are advised to set high expectation for their students' behavior and strictly enforce disciplinary measures (Baumert et al., 2010). Time management skills are vital in cognitively challenging classrooms because teachers are expected to cover the same course content as their counterparts whose classes do not experience "interpersonal conflicts" or "disruptions" on a daily basis (Bishop Smith et al., 2012).

According to the OECD report (2014) which compared the use of cognitive strategies in mathematics with low ability, medium ability, and high ability students, low and medium ability students gain more confidence when cognitive strategies assisted them in translating abstract mathematical statements into statements they could understand easily. Cognitive activation strategies in mathematics classrooms enable students to have more control over their applications of mathematics concepts to solve problems. Furthermore, students who utilize cognitive activation strategies are inclined to value the course content, thus gaining autonomy over their learning processes, and their motivation to learn is likely to increase (Burić, 2015). By contrast, lack of cognitive activation strategies among students leads to their frustration, anxiety, and boredom (Burić).

Instrumental Motivation to Learn Mathematics

"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 their future plans involve application of mathematics concepts or learning mathematics will enable them to advance their career interests. Students' positive image of ideal self, external influence, positive attitude towards a subject and the enjoyment of learning a subject are some of the factors which inspire instrumental motivation among students (Dailey, 2009; Middleton & Spanias, 1999; Pitsia et al., 2016; Tella, 2007).

Students' positive image of ideal self is what a student would like to be in the future (Dailey, 2009; Linder, Smart, & Cribbs, 2015; Pitsia et al., 2016). For example, a student who intends to peruse a major or career in Science, Technology, Engineering and Mathematics (STEM) is instrumentally motivated to excel in mathematics and science in high school because STEM courses are prerequisite for advanced courses (Dailey, 2009; Middleton & Spanias, 1999; Pitsia et al., 2016). A comparison study of instrumental motivation between Turkish and Vietnam students' found that Turkish students were instrumentally motivated to pursue mathematics and science partially because Turkish students were encouraged to choose their majors earlier than their counterparts in Vietnam (OECD, 2014). Additionally, Turkish students found connections between mathematics and science concepts in their daily lives with relative ease than Vietnamese students (OECD).

Second, instrumental motivation among students is inspired by students' positive attitudes towards a subject (mathematics) (Else-Quest et al., 2010; Novak & Tassell, 2017). Positive attitudes towards a subject are manifested by learning practices which encourage positive student-teacher relationship (Linder et al., 2015). For example, in a learning environment where students are free to seek help, and the teacher is receptive to students need. In this learning environment (positive attitudes) students tend to value the subject and they strive to gain "control" of the subject as explained in the value and control theory (Pekrun, 2006). Students who are instrumentally motivated to learn mathematics participate in their learning actively (Areepattamannil, 2014). For instance, they ask questions and/or clarifications, tend to have better mathematics work ethics than their counterparts who do not plan to pursue mathematics or mathematically related majors and careers.

Third, instrumental motivation is improved by students' enthusiasm for mastering a subject content (Dailey, 2009). Students who are dedicated to learning a subject (mathematics) are self-driven to excel in the subject (Chang et al., 2016 & Pitsia et al., 2017). These students enjoy challenges poses by a subject and pride themselves in excelling in the subject tend to devote extra time to study, seek help whenever necessary, they overcome setbacks faster than their counterparts who do not enjoy the subject and they also try new challenges (Areepattamannil, 2014; Garon-Carrier et al., 2016; Linder et al., 2015; Pitsia et al., 2016).

According to Dailey, (2009) external influence or having high expectation of students' performance plays a vital role in fostering instrumental motivation among students. Dailey, mentioned that parents, teachers and student peers are potential sources of external influence. External influence (friends and family) serves as a role model to the students, a source of inspiration in difficult times and "unofficial" academic advisor on career and major selection (Areepattamannil, 2014; Dailey, 2009; Linder et al., 2015; Pitsia et al., 2016).

Finally, OECD (2014) found that instrumental motivation levels among female students were below their male counterparts in Australia. However, the overall instrumental motivation level for Australian students was above the OECD average. Additionally, OECD found that Singaporean, United Kingdom, New Zealand, Canada and, Australia students were the top five countries which had the highest levels of instrumental motivation to learn mathematics. Students from low socioeconomic status schools had a higher level of instrumental motivation compared to students from high socioeconomic status schools.

Mathematics Anxiety

Mathematics anxiety is defined as "a feeling of tension, nervousness and/or worrying about failure" that interferes with the manipulation of numbers and the solving of mathematical problems in . . . ordinary life and academic situations" (Richardson & Suinn, 1972). Also, mathematics anxiety brings a sense of helplessness to individuals (Maloney et al., 2014). Individual who feel helpless believe that success is out of their grasp, and they attribute their failure to internal factors to such an extent that learned helplessness often becomes perceived as a stable and unchanging trait (Braver et al., 2014). According to Maloney, Sattizahn, and Beilo, helpless individuals are not motivated to undertake challenging tasks: in fact, when facing a challenging task, they underperform. According to the PISA 2012 report, 59% of students surveyed doubted their ability to excel in mathematics classes, and 30% felt helpless when doing a mathematics problem.

Mathematics anxiety becomes worse as students age and progress to higher grades (Artemenko et al., 2015). A longitudinal study conducted in the United Kingdom surveyed students on mathematics anxiety in primary schools (middle school) and high school and found an increase in the level of mathematics anxiety experienced by high school students compared to middle school students (Dowker et al., 2016). Several reasons were given to explain this study’s findings. First, students in high school were better informed about the consequences of failure in mathematics for their career options later in life. Additionally, students who experienced mathematics anxiety were worried about limited choices in STEM majors at college, a factor that many students are not concerned about in middle school. The majority of students tended to compare themselves with high-achieving students rather than with lower-achieving students in their classes, school, districts, states, or country. High-achieving students felt the need to improve or maintain high scores whereas low-achieving students worked hard to better their scores.

Third, students’ attitudes towards mathematics also contributed to the level of mathematics anxiety that students experience (Artemenko et al., 2015). High school students’ attitudes towards mathematics are relatively formed compared to middle school students’ attitudes, which are evolving as they comprehend the subject and realize the relationship between their mathematics scores and career goals. According to Artemenko et al., students who had a positive attitude towards mathematics experienced less mathematics anxiety compared to their counterparts who exhibited negative attitudes towards mathematics.

The challenges of mathematics anxiety among high school students affect students from diverse backgrounds (Lee, 2009). Lee's study examined mathematics anxiety among high school students from forty-one PISA participating countries. The study found that the relationship between the level of mathematics anxiety and mathematics performance was unreliable. For example, students from Asian countries like Japan, South Korea, Hong Kong, and Singapore experienced high levels of mathematics anxiety. By contrast, students from Western European countries such as Switzerland, the Netherlands, Finland, and Liechtenstein demonstrated low levels of mathematics anxiety. Students from both regions, however, excelled in PISA mathematics and science tests consistently in the past three testing cycles.

Two explanations of Lee's findings have been suggested. First, the mathematics curricula in Asian and Western European countries partly contributed to Asian students' anxiety in mathematics (Chauvot, 2008; Kim et al., 2011; Pehkonen, 2008; Sastre-Vazquez, D'Andrea, Villacampa, & Navarro-Gonzalez, 2013; Siraj-Blatchford & Nah, 2014; Woodward & Ono, 2004). Students in Western European countries were allowed to select their majors in the first year in high school, reducing the number of subjects that were tested. Whenever students are given a choice, they tend to choose subjects that interest them and in which they excel (Villacampa, & Navarro-Gonzale). A study that compared the study habits of students in South Korea and Finland found that students in Finland surpassed because they specialized in few subjects early in their academic careers among other factors. Specialization gave students adequate time to master the subject content.

Mathematics anxiety levels were lower among students in Finland than the Asian countries (Pehkonen, 2008). High parental expectations of Asian students and intensive competition to secure entry in selective universities (STEM-oriented) are some of the factors which contribute to their continued success in mathematics, although mathematics anxiety levels were relatively higher compared to their counterparts in Western European countries (Kim et al., 2011). According to (Kargar et al., 2010), the difference in mathematics anxiety levels between minority and white students were not statistically significant in the United States. Students' race, ethnicity, or religious afflictions were not directly related to fluctuations in their mathematics anxiety (Ashcraft, 2002; Else-Quest et al., 2010; Lee, 2009; Maloney et al., 2014).

Adolescent girls have exhibited slightly higher levels of mathematics anxiety than boys in countries where both boys and girls are given equal opportunities to pursue their academic and career goals (Else-Quest et al., 2010; Stoet et al., 2016). However, in countries or families where the girl child is not encouraged to pursue mathematics or where she lacks a role model, girls self-reported significantly higher level of mathematics anxiety than boys (Harari et al., 2013). Several studies (Artemenko et al., 2015; Novak & Tassell, 2017; Stoet et al., 2016) found that mathematics anxiety differences between boys and girls decreased as they grew into early adulthood.

Mathematics anxiety is negatively related to students' performance (Maloney et al., 2014). Anxiety makes students doubt themselves, therefore diverting valuable time and energy meant for learning (solving mathematics problems) to worrying (Artemenko et al., 2015). The effects of mathematics anxiety start early in students' academic careers and progressively become worse if no remedial measures are taken (Artemenko et al., 2015; Dowker et al., 2016; Pehkonen, 2008).

Mathematics Work Ethic

Mathematics work ethic as a research construct is relatively new (Meriac, 2012). This construct was used for the first time in 2012 assessment cycle. However, in the recent past researchers have devoted considerable resources to the study of motivational and affective factors that affect student performance. Mathematics anxiety, motivation for learning mathematics, the social and economic status (SES) of students' families, and students work ethics are examples of motivational and affective factors that affect students' mathematics performance (Areepattamannil et al., 2016; Dowker et al., 2016; Meriac, 2012; Middleton & Spanias, 1999). Meriac, Poling, and Woehr (2009) defined work ethics as "not a unitary construct, but a constellation of attitudes and beliefs pertaining to work behavior." They also noted that work ethics are not related to individual intelligence, gender, or faith, but they are strictly related to the personal engagement and enjoyment that a person derives when performing a task and anticipating rewards upon its completion:

> Work ethic is multidimensional, and it is comprised of seven components: (a) centrality of work, a belief that work is vital in its own right, (b) self-reliance, representing a drive toward independence in task accomplishment, (c) hard work, a belief that increased effort is the key to achievement, (d) leisure, a value on downtime/non-work activities, (e) morality/ethics, a proclivity to engage in just/moral behavior, (f) delay of gratification, the capacity to postpone rewards until a later time, and (g) wasted time, the importance of the efficient use of time (Meriac, 2012,p.85).

Therefore, mathematics work ethics refer to a student's ability to dedicate time, hard work, and persistence, among other components of work ethics, to attain mathematics competency.

Cultural beliefs play a significant role in the development of students' work ethics. Jerrim's (2015) study compared the work ethics of students in North American countries with their counterparts in East Asia countries to find out if students' work ethics were a contributing factor in the exemplary performance of East Asian students' performance on PISA tests. Jerrim found that work ethics were instilled in students at a young age in the East Asian countries. For example, the majority of students in East Asian nations devoted about twelve hours a day to in-school and in after-school learning activities (tutoring). They counterparts in North America spent fewer than eight hours in school. Additionally, East Asian students persisted (i.e., they attempted a mathematics problem) several times before seeking help. Asian students derived a sense of pride and affirmation from their efforts even when they did not accomplish their goals in the first attempt. On the contrary, North American students were impatient, less motivated, and not willing to try “hard enough.” Along with the introduction of works ethic at a young age, sustained efforts are required to encourage students to keep working hard and internalize these sound work ethics. Parents and teachers should hold students to high expectations and support them in the achievement of their goals (Jerrim, 2015).

Results from several studies (Areepattamannil et al., 2016; Jerrim, 2015; Meriac et al., 2009; Rosenthal et al., 2011) were inconclusive about whether work ethic strategies are transferable across study domains. For instance, there was no relationship between the work ethics required to play computer and video games and the work ethics needed to study mathematics and sciences. Although playing games and studying mathematics and sciences requires skillful manipulation of several variables as well as persistence, students' ability to withhold gratification was the primary differentiating factor in their mathematics success. According to Meriac et al. (2009), students work ethics when playing games were at a high level because the rewards of playing the game were achieved at the end of the game (within a shorter duration) but were at a lower level when studying mathematics and sciences because the rewards of these pursuits are only realized after a more extended period.

Students' faith (religion), race, and gender are not related to their work ethics (Meriac et al., 2009; Rosenthal et al., 2011). Furthermore, Rosenthal et al. (2011) explained the Protestant work ethics as a "social equalizer" and "a justifier of social inequality." The Protestant work ethic refers to the belief "that people from all social categories have equal potential to succeed through hard work and effort" (p.56). Rosenthal et al. (2011) used the protestant work ethic framework to examine factors that contributed to enrolment disparities in Science, Technology, Engineering and Mathematics (STEM) majors and careers between men and female students and between African American and White students. Their study found that despite low expectations due to negative stereotypes and stigmatization of women's and African American's abilities to successfully pursue mathematics, the majority of students can excel in STEM majors if they are willing to work hard. On the contrary, high drop-outs and low graduation rates among women and African American students in STEM is sufficient evidence of lack of hard work, self-reliance, and emphasis on the centrality of work, which are important components of work ethic (Meriac et al., 2009; Rosenthal et al., 2011).

Student's mathematics work ethics are sustained by the confidence that they have in the outcomes of their efforts (Parkhurst et al., 2011). For example, students who believed that their efforts would be rewarded with good grades are motivated and engaged in learning. Additionally, motivated and engaged students tend to have higher levels of perseverance against challenging assignments, which leads to improved performance in mathematics (Meriac, Woehr, Gorman, & Thomas, 2013). However, students with low persistence and lack of confidence in their hard work tended to develop negative attitude towards mathematics, to lack motivation, and to disengage (loss of control) from the learning process; consequently, it leads to poor performance in mathematics. Mathematics work ethics is not related to students' intelligence (Meriac et al., 2009); therefore, low performing students can be mentored to improve their work ethics and, possibly, to improve their mathematics scores as well. Similarly, high performing students can be distracted by their circumstance and adopt poor work ethics.

Gender

According to Ziegler et al., (2014), gender differences have disappeared in many educational settings, yet male and female students remain strongly segregated in science, technology, engineering, and mathematics (STEM) majors and STEM-related careers. Several factors have contributed to the narrowing or widening of the gender gap in different countries. For example, cultural biases against female children, lack of role models for girls and women, fewer career opportunities for women compared to men in STEM, low self-confidence to pursue mathematics and sciences, and higher mathematics anxieties among girls than boys are some of the challenges on the path that girls take towards closing the gender gap in mathematics and sciences (Abu-Hilal et al., 2014; Else-Quest et al., 2010; Halpern et al., 2007).

The gender gap in mathematics and science begins in middle or high school and gradually widens at institutions of higher learning (Ziegler et al., 2014). According to a meta-analysis by Else-Quest et al. (2010) that compared the performance of boys and girls in several countries using the Programme for International Student Assessment

(PISA) data, the study found a negligible gender gap in mathematics and sciences performance among middle and elementary school students. Some practices widen the gender gap without the express knowledge of the perpetrators. For example, in studies that monitored students' participation in mathematics and science classes found that teachers chose more boys than girls to respond to their questions, offer suggestions, or demonstrate how to solve problems in front of a classroom even when an equal number of students from both genders were willing to volunteer (Else-Quest et al., 2010; Stoet et al., 2016).

In a similar study, Halpern et al. (2007) found that boys were frequently elected leaders of mathematics, science, and computer classes more than girls. In contrast, Halpern et al. observed that girls lead writing and drama clubs more frequently than boys. Xu (2015) mentioned that male computer game characters "always" succeed in STEM careers. For example, male characters were engineers, astronauts, and surgeons while women thrived in hospitality industries. Subconsciously, a practice that portrays boys and men as superior in STEM majors or careers reinforced the stereotype that "girls and women are not as capable in doing mathematics and science as men." Also, these practices are contributing to efforts geared towards closing the gender gap in mathematics.

Gender differences in mathematics and sciences are not restricted to students in the North American countries: It is a global challenge (Stoet et al., 2016). In many developed countries, the implementation of affirmative action has gradually corrected gender imbalances in schools and workplaces. The enactment of affirmative action has increased opportunities for women and minorities to pursue careers in STEM. However, in many developing countries, believes that "value" a boy child more than a girl child still thrive. In many developing countries, jobs or income generating opportunities are limited (Areepattamannil et al., 2016; Jerrim, 2015; Schulz, 2005). For example, developing countries have fewer schools compared to student demand, their tuitions are high, and they have scare financial assistance for education. Additionally, the majority of the citizens of developing countries struggle economically, and whenever resources are scarce, boys are prioritized over girls for access to educational opportunities (Abu-Hilal et al., 2014; Stoet & Geary, 2013). Boys are encouraged to pursue STEM majors that promise stable and lucrative rewards (Else-Quest et al., 2010). This prioritization of boys over girls in the distribution of resources and opportunities is a true reflection of the decision making process in many developing countries' cultures, where men make most of the decisions (Else-Quest et al., 2010). However, with the rapid spread of education, the culture of the "strong man" is changing, and more girls are accessing and excelling in school (Burić, 2015).

Students' attitudes towards mathematics, self-beliefs in mathematics, and mathematics anxieties are significantly related to their performance in mathematics (Novak & Tassell, 2017; Pitsia et al., 2016; Reilly et al., 2015). In several studies (Lazarides, Rubach, & Ittel, 2017; Linder et al., 2015; Pitsia et al., 2016) on students' attitudes, self-beliefs, and anxieties towards mathematics and science in middle and high school, girls self-reported lower scores than boys. Positive attitudes and self-beliefs towards mathematics were related to a high motivation to study mathematics (Areepattamannil, 2014; Tella, 2007). Low mathematics anxieties were associated with students' enjoyment of and engagement in learning mathematics and sciences. The

Institute of Physics in the United Kingdom survey (2012) found that mathematics was the fourth favorite subject for boys but the nineteenth most popular among girls.

Lack of role models at home and school for girls have also been cited as possible obstacles towards closing the gender gap (Else-Quest et al., 2010; Halpern et al., 2007; Shafiq, 2013). Jerrim (2015), who compared mathematics performance of second-generation Asian students who migrated to Australia with their non-migrant counterparts (Australians), he found that Asian students performed better than their peers partly because they were practicing better mathematics work ethics. Besides, the majority of these students had parents or sibling working in or pursuing careers in STEM fields who encouraged and motivated them to overcome learning challenges. Low graduation rates for female compared to male students in STEM make it harder for schools and universities to recruit and retain female teachers and professors in STEM subjects (Cantley et al., 2017; Ziegler et al., 2014). Second, STEM graduates (male and female) are lured away from teaching by lucrative pay, better working conditions, and the prospect of rapid career growth in other industries (Halpern et al., 2007; Shafiq, 2013; Stoet et al., 2016). Further,

> Women are also underrepresented in academic positions at research universities, especially in science and mathematics. A recent review found that women in science, engineering, and technology are less likely to obtain tenure (29% of women compared to 58% of men in full-time, ranked academic positions at 4-year colleges) and are less likely to achieve the rank of full professor (23% of women compared to 50% of men) (Halpern et al., 2007,p.8).

Shafiq (2013) mentioned that, deliberate efforts aimed at narrowing the gender gap in mathematics—like hiring more female teachers and professors to teach mathematics and sciences, rewarding female teachers and professors at par with their male counterparts, and encouraging students to pursue STEM courses at a young age by attending science fairs or participating in mathematics and sciences competitions—were bearing fruit, but at a slow pace. Additionally, the PISA report (2014) indicated that the gender differences in mathematics and science test scores of students aged 15-16 years old have fallen in the previous consecutive eight years.

Finally, the notion that boys and men excel in mathematics and science because they are naturally smarter than girls and women has been disapproved by several studies (Else-Quest et al., 2010; Halpern et al., 2007; Stoet et al., 2016).

Social and Economic Status (SES)

Students' socioeconomic backgrounds play a significant role in determining their access to learning resources. According to OECD (2014), parents' level of educational, parents' occupational status, and parents' household possessions are some of the factors used to assess parents' social and economic status. Household assets, for example, the number of cars, electronic devices (televisions, phones, and computers) a family owns. According to OECD (2014), household possessions tend to assess a family wealth better than income. For instance, parents who are college graduates (holding a Bachelor's degree or higher), especially in Science, Technology, Engineering, and Mathematics (STEM) fields tend to serve as role models to their children who decide to pursue STEM studies (Merola, 2005). Jerrim (2015) compared the performance of the second-generation children of Asian immigrates born in Australian with children of nonimmigrant Australians in mathematics and science and discovered that the second generation students of Asian descent had better work ethics. Also, second-generation children whose parents were in STEM-related careers outperformed their counterparts (Asians and Australians) whose parents had careers or educational background in non-STEM fields. Parents or guardians in STEM careers are role models to the students in mathematics and science whom they inspire, motivate, and assist.

On the contrary, the majority of parents with low education struggle in mathematics (Ferguson, 2008). Additionally, students adopt negative altitudes against mathematics from their parents, guardians, or peer influences (Pitsia et al., 2016). Parents who respond to students' inquiries with negative stalemates like, "I don't like mathematics," "I am not good with numbers," and "You will never use these formulae after this course" when their children seek help or advice on mathematics sow seeds of discouragement, lacking self-belief in their own ability to do mathematics (Areepattamannil, 2014; Meriac, 2012; Rosenthal et al., 2011; Tella, 2007). Additionally, students use these excuses to justify their lack of motivation and to embrace a defeatist attitude towards mathematics (Abu-Hilal et al., 2014; Lazarides et al., 2017; Merola, 2005).

The occupational status of parents is a relatively good indicator of family income (OECD, 2014). For example, a household where the mother is an engineer and the father is a doctor is expected to have a higher income than a family where the father is an unskilled employee, and the mother stays at home. Parents with higher financial support tend to provide their children with the necessary learning resources for academics success (Schulz, 2005). Students from high-income families are exposed to cognitive activation at a tender age and tend to have better vocabularies, spell more words, and accurately perform more basic arithmetic operations before enrolling in the first grade than their counterparts from financially less stable families. Furthermore, parents who are economically stable are more likely to provide an academically enabling environment at home. For instance, these students often have access to books and magazines that cover a broad scope of topics at home, in community libraries, or through their parents' subscriptions. Financially stable parents are likely to enroll their children in private schools or public school in high-income neighborhoods, which more experienced teachers, lower student-teacher ratios, and lower teacher turnover rates than public schools in low-income communities, where the majority of students from financially unstable families enroll. Therefore, students from higher income households have more resources at their disposal to overcome academic challenges.

The collection of accurate information on parents' education is a significant research challenge (Areepattamannil et al., 2016; Merola, 2005; Schulz, 2005). For example, students being surveyed may not know or recall their parents' level of education. Likewise, parents may not disclose their education levels for private reasons or out of concern that the data may be used against them. Furthermore, when education level data are collected in different countries, a common measure like PISA could be used to facilitate comparisons between participants from different countries and education systems.

Ascertaining the accuracy of self- reported income information is almost impossible (Areepattamannil et al., 2016; Merola, 2005; Schulz, 2005). First, individuals are usually reluctant to disclose their sources of income and their total incomes. Second, financial documents at the human resources office might not portray certain person incomes because an individual may have multiple incomes that are not reflected in human resource records. Third, remuneration in the formal employment system obeys the law of supply and demand. For instance, science and engineering workers in developed countries with a high number of STEM graduates may not attract the same pay as their counterparts in developing countries where such skills are scarce.

Although the means of assessing individuals' social and economic status (educational level of parents, occupational status of parents, and home possessions) have these shortcomings that could influence a study's findings when raw data is used, statistical methods have been applied to obtain reliable data (Schulz, 2005).

Mathematics and Science Performance

At the inception of the PISA assessment, test participation was limited to OECD countries. Gradually, other countries and economies were allowed to participate. Therefore, in many PISA reports, data are presented in two categories (OECD countries and non-OECD countries). For example, the mathematics performance of students in OECD countries versus the performance of students from non-OECD countries or "All participating countries/economies" has combined effects on OECD and non-OECD countries and economies. According to PISA report (2012), majority of students were low performers in mathematics, comprising 65% of all low performers. Also, 15% performed below the proficiency levels in science. In total, mathematics and science accounted for 80% of low performers.

Students' low performance in mathematics and science is attributable to several factors. These factors can be classified into two broad categories: home and school environments. Learning begins at home (Meriac, 2012; Park & Hill, 2016; Quinn, 2014), and parents or guardians are expected to instill values in students before they enroll them in the formal learning system (Gastón, 2011). For example, students are expected to learn to obey and respect authority figures in society and to develop a positive attitude towards learning and proficiency in basic communication skills before joining school or soon after. These skills are necessary for students to thrive in school.

Students’ disrespect for teachers and peers leads to behavior problems that distract teachers from their engagement in learning activities (Cheon et al., 2016). Whenever disciplinary measures are taken against distractive students in a classroom, valuable learning time is lost because mathematics and science content is taught in a linear format (Caughy et al., 1994; Lam & Lau, 2014; McConney & Perry, 2010). This linear organization of the course content ensures that students learn the basic concepts before advanced concepts are introduced. Regular absenteeism also breaks the linear format of learning in these classrooms and interferes with the acquisition of vital concepts that will become necessary in future classes.

Students’ behaviors in classes, meanwhile, are also closely associated with their attitudes towards the subject (Kargar et al., 2010; Pitsia et al., 2016; Rosenthal et al., 2011). Well behaved students tend to exhibit positive attitudes towards learning, are motivated to learn, have better work ethics, and tend to persist against challenging situations. In contrast, distracted students display negative attitudes towards learning, disengage from learning, and tend to give up easily (Braver et al., 2014; Garon-Carrier et al., 2016; Tella, 2007).

Indeed, several researchers (Areepattamannil et al., 2016; Braver et al., 2014; Meriac, Thomas, & Milunski, 2015) have shown that students' attitudes are related to their performance. Pitsia et al.'s (2016) study, which compared students' attitudes, motivation, and self–beliefs in their ability to learn mathematics with their performance in mathematics, found that students who had positive attitudes and high levels of self-belief in learning mathematics were highly motivated and performed better than their counterparts who had negative attitudes and low confidence in their ability to solve mathematical problems.

Students' negative attitudes and lack of confidence in their abilities to learn mathematics and science can be changed for the better (Areepattamannil et al., 2016; Burić, 2015; Else-Quest et al., 2010). Supportive learning environments at home and school are vital agents behind changing students behavior and attitudes (Areepattamannil et al., 2016). Parents and teachers should hold students to high expectations by continually challenging them to do "more" and by encouraging them to try to solve a problem several times without giving up. Likewise, parents and teachers should avail students of extra learning assistance, such as tutorial services in and after school.

Table 1

Low Performers in Mathematics, Reading, and Science in Economic Co-operation and Development (OECD) Countries and in all Participating Countries/Economies

OECD Countries			All participating countries/economies		
Subjects	Number of Students	Percentage	Percentage	Number of Students	Subject
Mathematics	948,423	65	65	2,127,165	Mathematics
Reading	304,742	20	20	659,939	Reading
Science	216,662	15	15	483,912	Science
Total	1,469,827	100	100	3,271,016	Total

Note. Adapted from OECD report 2014

Teachers should also be mindful to assign appropriate homework on topics covered in class or prerequisite courses (Chauvot, 2008). According to studies which have examined students' cognitive activation in mathematics classes (Areepattamannil et al., 2016; Baumert et al., 2010; Bishop Smith et al., 2012), students persisted on challenging assignments, were more engaged in the classroom, and were less anxious about test-taking when they were dealing with course content covered in class or content to which they could relate. For instance, high school students were likely to read or attempt to solve problems ahead of current topics if textbook examples were written in "plain English" as opposed to abstract definitions and proofs in mathematical symbols. Similarly, teachers' displays of caring attitudes and genuine concern for students' academic success motivates students (Garon-Carrier et al., 2016). Caring teachers created a friendly learning environment in which students were unafraid of making mistakes or seeking help (Uche, Kaegon, & Okata, 2016).

Students' performance in general and in mathematics and sciences, in particular, are also affected by policymakers at the national, state, and district levels. Policymakers influence the distribution of resources that facilitate learning, for instance (Kim et al., 2011; Novak & Tassell, 2017; Uche et al., 2016). Another example, mathematics and science teacher shortages disproportionately affect students in low socioeconomic school districts. Individual school districts' efforts to address this shortage may not yield the desired results because of limited resources, but changes in federal and state policies are likely to yield better solutions to the recurrent problem. According to the PISA report (2012), qualified mathematics and science teachers leave low socioeconomic school districts because of poor working conditions and better opportunities afforded elsewhere. "Rigorous research has found that high-performing teachers don't only help their students do better on the standardized tests everyone loves to hate; their students also graduate from college at a higher rate and earn more money as adults. Great teachers, quite simply, change lives" (Green, 2010,p.21). Policymakers could create incentives to attract and retain qualified teachers in underserved locations.

Plausible Values

The PISA dataset uses a planned missing data design so that students are not tested on all items on the PISA mathematics and science test. Multiple imputation methods are used to generate plausible values where there are missing data points.

To help explain plausible value, suppose there are five hundred cars of different colors in a college parking lot in a week, and I want to know the number of white cars among those five hundred cars. Instead of counting all the white cars, a random sample of fifty cars of different colors that represents the whole population can be selected, then the number of white cars in the sample on Monday, Wednesday, and Friday can be counted to produce an estimate. The number of white cars parked on Tuesday, Thursday, Saturday, and Sunday can be computed assuming all factors stay constant using the data and statistical methods like linear regression. This sampling approach saves time because there are fewer white cars in the sample size compared to the whole population. Second, the sampling approach has the potential of saving labor costs. For instance, counting white cars among the total population of five hundred may require two or more persons to count simultaneously or recount to confirm. However, the sampling approach is relatively susceptible to errors compared to counting the white cars from the whole population.

The derivation of plausible values closely follows the car sampling illustration. Wu (2005) defined plausible values as “values which represent the range of abilities that a student might reasonably have, given the student's item responses” or “multiple imputations of the unobservable latent achievement for each student, (p.13).” Likewise, “plausible values can be viewed as a set of special quantities generated using a technique called multiple imputations” (Davier, Gonzalez, & Mislevy, 2009, p.27).
Suppose a mathematics department wants to find the proficiency level of sophomore students in calculus at the end of the sophomore year. In this department, calculus content is divided into two parts: Calculus I, which covers nine chapters, and calculus II, which includes another nine sections. The department needs about three hundred minutes to test the central concepts of calculus I and II compressively. In order fit the testing time into the university schedule and spare students the "agony" of spending three hundred minutes taking a calculus test., the calculus instructors decided to divide the test into six blocks.

Each block has twenty randomly sampled questions from calculus I and II coursework, and students are allowed fifty minutes to solve problems in each block.

Table 2

Six Blocks Combined into Two-Block Booklets

	Booklet					
Blocks	1	2	3	4	5	6
Part I	A	B	C	D	E	F
Part II	B	C	D	E	F	A

Note. Adapted from Davier et al., 2009

Each student is required to take one block of the test (part I & II), answering forty questions in a one hundred minute timeframe. Each block of the test (A-F) occurs once in part I and II. The blocks are partially linked. For example, block 1 starts with tests A & B, block 2 has tests B (linking block 1 with block 2) and C, and block 6 contains tests F and test A (link block 6 to block 1). This design of testing is called the rotated test (Monseur & Adams, 2009).

The mathematics department can generate plausible values to assess the calculus proficiency of each student who took the tests using students' scores from the shorter version of the calculus tests and statistical methods like maximum likelihood and weighted estimators. Three or five plausible values can be generated for each student to accommodate a wide range of students' capabilities. For example, a student who scored 80% on the sample test may have plausible values in the range of ± 5%, 75% (lower limit), 80% (median), and 85% (upper limit). Five plausible values were generated per subject (mathematics, science, and reading) for each student who participates in the PISA test.

According to Wu (2005, p.8),

> The theory and use of plausible values were first developed for the analyses of 1983-84 at the U.S. National Assessment of Educational Progress (NAEP) data, by Mislevy, Sheehan, Beaton, and Johnson. Plausible values were used in all subsequent NAEP surveys and surveys such as the Third International Mathematics and Science Study (TIMSS) and the Programme for International Student Assessment (PISA).

The Program for International Student Assessment (PISA) implements a rotated test design to facilitate the testing of fifteen to sixteen-year-old students from forty-four countries. The total population of fifteen to sixteen-year-old students eligible to participate in the PISA tests in 2012 was 28 million. In the year 2012, 510,000 students participated in PISA tests measuring mathematics, science, and reading proficiency. "The purpose of a study such as PISA is to describe the characteristics of populations of the 15-year-old students in school. That is, the assignment of valid and reliable scores to individuals is not a purpose of PISA" (Monseur & Adams, 2009,p.10).

Despite the logistical challenges posed by the administration of the PISA test because of the huge numbers of students who participate in PISA test, statistical methods and models are used to generate plausible values, plausible values cannot be used to replace scores of a “true score” (scores obtained by a student who did all questions in a test) because two students with the same “true scores”) cannot have the same plausible values (Monseur & Adams, 2009; Davier et al., 2009; M. Wu, 2005). Furthermore, averaging plausible values for each student and using the average for further analysis leads to biased results. Instead, each student's plausible values should be analyzed individually and then calculate the average the results of all plausible values (PISA, 2012).

However, plausible values are valuable in describing the proficiency levels of populations of the 15-year-old students in school. According to Monseur & Adams, (2009), "Plausible values are intermediate values that are provided so that consistent estimates of population parameters can be obtained using standard statistical analysis software such as SPSS and SAS" (p.11).

National Context of the Study: Education in Australia

In the 1980s and early 2000s Australian students (primary and secondary school) performance in mathematics and science was exemplary (Thomas, 2011). According to Thomas, who analyzed developments in mathematics education in Australia from 1980-2011, Australian students excelled in mathematics and science regionally as well as internationally between the 1990s to early 2000s. For example, in 1995, Australian students, year 4, (middle school) were ranked number 10 in mathematics and position 5 in science respectively out of 34 countries which participated in the Trends in International Mathematics and Science Study (TIMSS) assessments. TIMSS is a series of international assessments of the mathematics and science knowledge of students around the world and is conducted every four years (Malone & Haimes, 1999; Mullis & Martin, 2014). Additionally, Australian students, year 4, who were ranked number 10 in mathematics in 1995 recorded a slight improvement in 1999 TIMMS assessments in year

8 (high school), they were ranked number 9 out of 17 countries who participated in TIMMS 1995 and 1999 (Malone & Haimes, 1999).

The Organization for Economic Co-operation and Development (OECD) is an intergovernmental economic organization. The organization attracts membership from 32 countries. The majority of the OECD member nations are in Europe, East Asia, and North America. In addition to collecting and analyzing data to monitor the economic progress of each OECD member nation, the organizations assess 15 and 16-year-old students' competencies in mathematical literacy, scientific literacy and reading literacy triennially. The Programme for International Student Assessment (PISA) formulates, administers and analyzes assessment data on behalf of the OECD member nations.

Besides participating in international assessments, Australian students also participated and excelled in regional and international mathematics competitions either in groups or individually. In August 2006, Terry Tao, born and educated in Adelaide city in South Australia won the prestigious Fields Medal is the mathematics.

The Australian Education System

According to Ossiannilsson, Kess, & Belt (2012), the Australian education system, the system provides three levels of schooling: primary, secondary and tertiary. In Australia primary (Kindergarten and Preparatory) runs from Year 1 to Year 7 (Grade 1 to Grade 7). Students take approximately seven to eight years to graduate. The majority of students begin primary school at six years old. Secondary school (high school) runs from Year 7 to Year 10. The senior Secondary school runs from Year 11 to Year 12. Students in primary and secondary schools sit the National Assessment Program (NAP) test in Years 3,5,7,9. NAP assess students' competencies in numeracy and literacy, but the test has no impact on students' future schooling. However, NAP test data is used by the Australian government, education and school authorities to determine whether students are meeting important learning objective. In Years 11 and 12 students prepare for the Senior Secondary Certificate of Education (SSCE). Upon successful completion of SSCE, Australian students can join a university or vocational education and training (VET). Students graduate from senior secondary school at age 16 to 18 years old. In Australia, primary and secondary education is compulsory. However, under the learning and earning law, students who are employed full-time after Year 10 are exempted. Students were instructed in English. English is the official language in Australia.

Despite the challenges experienced in mathematics and science the Australian education system has received favorable reviews locally and internationally (Ossiannilsson, Kess, & Belt, 2012). For example, in 2009 Australian, OECD average and the United States annual spending per high school student were $ 8639, $8746 and $11,788 respectively (OECD). Furthermore, in 2009 PISA results, Australians students performed better than the OECD average and their United States counterparts in reading, mathematics, and science. In reading, Australian students had a mean score of 515; the United States mean score was 500, and the OECD average was 493. Australian students recorded a mean score of 514, OECD average was 496 and United States mean score 487 in mathematics. Finally, Australian students had a mean score of 527, United State 502 and OECD average was 501 in science.

Australia graduates 71% of high school students and has implemented better school-to-work programs in the vocational training schools than many developed countries (Stolz, Hendel, & Horn, 2010). Additionally, Australia is rapidly closing the achievement gap between indigenous and non- native students, students from low-income and high-come families and among girls and boys (Jerald, 2008; Ossiannilsson et al., 2012; Stolz et al., 2010). Epper (2011) mentioned that federal and states governments had increased resources and mentorship programs to support initiatives aimed at ending achievement disparities.

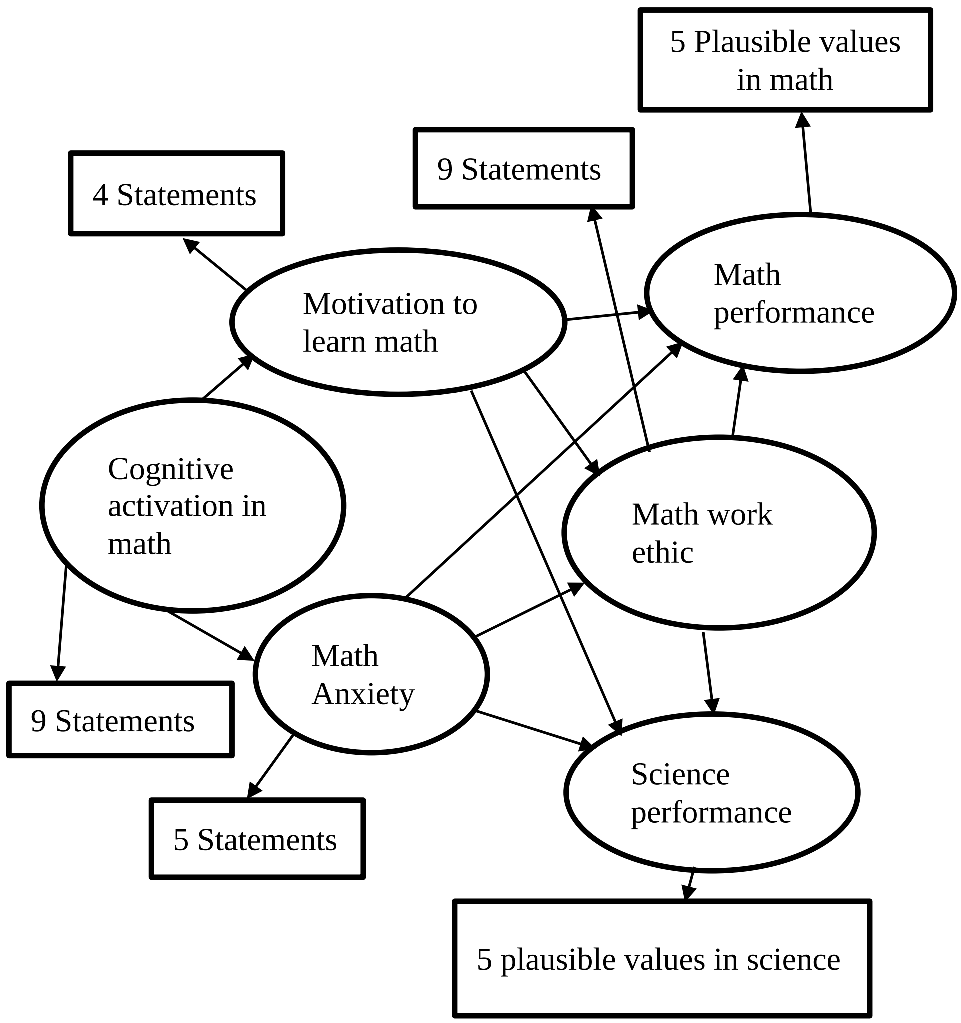


Figure 1. The Hypothesized Path Model was Developed to Test the Relationships among the Study Variables

Research Synthesis and Existing Gaps

Control-value theory guided this study. The theory explains that when students "gain control" of the subject content (understanding) they tend to value learning the subject. Furthermore, the control-value theory mentioned that when students value a subject, they are motivated to learn more about the subject which tends to increase the performance. On the contrary, students who "lack control" or students who struggle with a subject matter tend to dislike the subject. Disliking the subject encourages the developments of negative emotions like anxiety which are negatively associated with students' performance.

This study examines the relations among the following variables; cognitive activation in mathematics classes, mathematics anxiety, instrumental motivation to learn mathematics, mathematics work ethic, students' gender, and students' socioeconomic status. Although, some of the study variables have been extensively researched on in the past, for example, mathematics anxiety and students motivation in general. For instance, mathematics anxiety negatively affects students' mathematics and science performance. Likewise, motivation tends to inspire students' to learn the subject contents in-depth.

In this study relatively new variables like mathematics work ethic and a subset of motivation, instrumental motivation to learn mathematics were examined among other variables. The focus of this study is to find out if previously established relations, for example, mathematics anxiety and students performance will hold or change when the variables are analyzed together with other variables. Also, the moderation effects of mathematics anxiety and instrumental motivation by mathematics work ethic results will add to the existing literature because studies which combine this study's variables are relatively scarce. Finally, the use of structural equations model (SEM) data analysis method has the potential of highlighting new relations because of its advanced analytical capabilities.

Chapter II Summary

The theoretical framework guiding this study (control-value theory) and a detailed literature review of the study constructs (cognitive activation in mathematics classes mathematics anxiety, instrumental motivation to learn mathematics, mathematics work ethic, students' gender, and students' socioeconomic status) was done in chapter two. Also, the derivation of mathematics and science plausible values were illustrated. Likewise, strengths and weaknesses of plausible values were described. The suitability of using mathematics and science plausible values in this study was explained. The Australian education system (K-12) was described. Furthermore, declining performance in mathematics and sciences examinations (at local and international level) were enlightened. Finally, the hypothesized path model diagram was included in chapter two.

III: METHODOLOGY

Research Design

A correlational research design guided this study. According to (Whitley & Kite (2013), correlational research design is a quantitative method in which two or more quantitative variables are obtained from the same subject. This study has five independent variables: cognitive activation in mathematics, instrumental motivation to learn mathematics, mathematics anxiety, students' mathematics work ethics, students' socioeconomic status, and students' gender. Students' plausible values in mathematics and science literacy were the dependent variables.

This study examined the relations of cognitive activation in mathematics, instrumental motivation to learn mathematics, anxiety for mathematics (fear of failure or nervousness), mathematics work ethics as well as mathematics and science literacy performance. The mediational roles of instrumental motivation to learn mathematics, mathematics anxiety and, mathematics work ethic in the relationship between cognitive activation in mathematics and mathematics and science literacy performance among Australian students. The Structural equation modeling (SEM) method was used to analyze the data. Multi-group SEM analyses were conducted to find out if these relationships are invariant based on socioeconomic status (SES) and gender.

Participants and Sampling

The sample size is 4500 Australian students who participated in PISA 2012 assessments. Out of 4500, 2278 (50.6%) were boys, and 2222 (49.4%) were girls aged between fifteen and sixteen years old. About 1747 (39%) were students from low socioeconomic status and 2753 (61%) were students from high socioeconomic status.

Several reasons were considered in capping the sample size at 4500. The desirable ratio is 10:1, 10 or more participants for each independent variable (Suhr, 2006). Therefore, the sample size is sufficient for the intended analysis including interactions between variables. Second, data were not presented sequentially either by participants school or state. Therefore, the composition of this study's sample was chosen at random. Third, the gender ratio was relatively equal in the population data set was also reflected in this study's sample.

In PISA 2012 the minimal number of participants per country was between 4,300-5,000 students (OECD, 2014). Many countries randomly selected 150 schools and 35 students from each school to participate in PISA 2012 assessments, but Australian's participation in PISA 2012 was larger (775 schools and 14,481 students). Diversity in the sample was facilitated by including students from different backgrounds, jurisdictions, and gender.

The Australian PISA 2012 school sample consisted of 775 schools. The sample was designed so that schools were selected with a probability proportional to the enrolment of 15-year-olds in each school. Stratification of the sample ensured that the PISA sample was representative of the 15-year old population. Several variables were used in the stratification of the school sample including eight jurisdictions, school sector (Government, Catholic and Independent), geographic locations (Metropolitan, Provincial and Remote), sex of students at the school, a socioeconomic background variables (Indigenous and Non-Indigenous, Australian-born, first-generation, and foreign-born, English spoken at home and language other than English spoken at home) and an achievement variable (OECD, 2014, p.8-11).

Instruments

Context Questionnaire Development

The PISA 2012 conceptual framework for the context questionnaires was developed by consortium partners, participating in sampled schools and National Centers (OECD, 2014). The framework's objective was to develop instruments which to assess the cognitive and motivational and affective factors of students who participated in PISA assessments. Motivational and affective factors, for example, students' attitudes, motivation, and beliefs were measured by students' responses to a questionnaire. The National Centers were instrumental in variable naming, question construction, formulation of validation rules and the administration of the PISA 2012 assessment. Besides the paper-based questionnaire, there was an online school questionnaire (optional) which was intended to gather parents' information. Australia was among 11 countries which participated in the online school questionnaire (OECD).

According to OECD (2014), the item response theory (IRT) scaling techniques were applied in the construction of all assessments used to measure motivational and affective factors. The ConQuest software was used to generate item parameters (OECD, 2014). PISA 2012 constructs were calibrated and validated before they were administered. On average 750 students were randomly sampled from each participating country to take part in the calibration process. In total 31,500 students (500 students from each country) took part in the calibration process. The calibration of parent item parameters was done by merging student calibration samples with parent questionnaires (OECD). ConQuest software utilized the weighted likelihood estimate (WLE) method to generate student scores after the calibration. PISA 2012 was administered in Sixty-five countries, and around 510 000 students participated in the assessment. To enable comparison among students' perceptions and background and attitudes validation of questionnaire constructs is necessary (OECD, 2014).

Several methodological approaches were used to validate questionnaire constructs. First, the cross-country validity of the constructs was implemented to ensure accurate translation of questionnaire constructs from English or French into the language used for instruction in used in other participating countries. Also, "assumptions about having measured similar characteristics, attitudes and perceptions in different national and cultural contexts were outlined" (OECD, 2014, p.324). Second, the internal consistency of each scale within and between countries was established using Cronbach's alpha (OECD). Third, the reliability and correlations of related scales were estimated in each country.

PISA, 2012 student context questionnaires were administered in rotations. The rotation student context questionnaires approach was used for the first time in the PISA, 2012 assessment. This use of the rotation approach was meant to increase content coverage where keeping the survey taking time below 30 minutes.

The rotated design was such that three forms of the questionnaire contained a common part and a rotating part. The rotating portion which was administered to one-third of students included questions about attitudinal and other motivational and affective factors. Before using rotated student questionnaires in the main data collection, extensive analysis of the impact of this methodology on the continuity of the results was conducted. Results revealed negligible differences when means, standard deviations, percentiles were estimated using plausible values drawn with multilevel item response models that adopted different approaches to questionnaire rotation (OECD, 2014, p.58).

Table 3

Final Design of Rotated Student Context Questionnaires in PISA 2012

Form A	Form B	Form C
	Common part (8 minutes)	
Rotated question set 1 (11 minutes)	Rotated question set 3 (11 minutes)	Rotated question set 3 missing
Rotated question set 2 (11 minutes)	Rotated question set 3 missing	Rotated question set 2 (11 minutes)
Rotated question set 3 missing	Rotated question set 1 (11 minutes)	Rotated question set 3 (11 minutes)

Notes. The common part, which was administered to all students, contained demographics, home possessions, parental occupation and education questions.
Question set 1 contained items covering attitudes towards mathematics and the problem solving situational judgment test items.
Question set 2 included items on school climate and attitudes towards school.
Question set 3 consisted of items measuring Opportunity to Learn and learning strategies.
Adopted from PISA, 2012, p.61

Cognitive Assessment Design and Development

The PISA Governing Board supervises cognitive assessment designing, development, distribution and assessment and data collection of all PISA assessments. Also, the PISA Governing Board decides the structure of the test in terms of concepts (domain) to be tested and the scope of the test. The designing and development of mathematics literacy assessment took place between October 2009 and November 2010. The Mathematics Expert Group (MEG) working in collaboration with Achieve (USA) and Australian Council for Educational Research (ACER) were in charge of test designing and development process. The Mathematics Expert Group (MEG) held the first meeting in October 2009 where the review of previous PISA (mathematics test) done. Achieve piloted a survey and analyzed survey responses of mathematical content standards among high performing OECD countries which had participated in previous PISA tests. These countries included United Kingdom, Japan, Korea, Australia, Finland, and Ireland. After the analysis of survey responses from 34 countries and over 80 individuals (mainly mathematicians and mathematics educators), a revised framework draft was presented in 2010 and successive PGB meeting. The final version was adopted in 2011. The final framework was further validated by a team of mathematics experts who provided an independent external judgment after carefully reviewing the item pool to be used in PISA 2012.

The Australian Council for Educational Research (ACER) engaged nine test development centers namely ACER (test development division), the University of Melbourne (both in Australia), aSPe (University of Liege, Belgium), DIPF (Deutschen Institut für Internationale Pädagogische Forschung), IPN (Leibniz-Insitute for Science and Mathematics Education) and Heidelberg University (all three in Germany), NIER (the National Institute for Educational Policy Research, Japan), CRP-HT (the Centre de Recherche Public – Henri Tudor, Luxembourg), ILS (the Department of Teacher Education and School Research, University of Oslo, Norway) and ETS (Education Testing Service, United States) to prepare the mathematics test for PISA 2012. The broad team of test development centers brought diversity in terms of expertise, experiences, ensured that the PISA 2012 mathematics test was conceptually rigorous, cross-cultural and cross-national diverse (OECD, 2014). “The test development teams were encouraged to conduct initial development of items, including cognitive laboratory activities, in their local language. Translation to the OECD official languages (English and French) took place after items had reached a well-formed state” (OECD, 2014, p.26).

According to OECD (2014), mathematics test was organized into units based on common concepts. Each unit comprised of a stimulus (a text passage and a data table or a text passage and graph), a list of questions related to the stimulus and grading guideline (no credit, partial credit and full credit). In total, the PISA 2012 mathematics test had 56 units, 110 cognitive questions and the testing time was 270 minutes. The science assessment had 56 questions (18 units) and the testing time was 90 minutes. PISA 2012 science test was the same as PISA 2009 science test. Likewise, 36 out 110 mathematics questions were on previous tests in 2003, 2006, 2009. The remaining 74 questions were new. The 74 questions were selected from a pool of 172 questions which was developed by the testing centers and were pilot tested in all countries in 2011.

During the field trial, each testing center performed item analysis on mathematics test. The item analysis included item fit (the fit of items should be near to 1), item discrimination, item difficulty, distractor analysis, mean ability and point-biserial correlations by coding category (the point-biserial correlation for the key category should be positive and for the other categories much smaller or negative), differential item functioning (DIF) (analyses of gender-by-item interactions and item-by-country interactions) and item omission rates (OECD, 2014). After incorporating feedback from the field trials (pilot tests), Achieve performed an independent external validation of the mathematics test and concluded that "... that the items represent the framework well, and cover the mathematics expected of 15-year-olds at an appropriate breadth and depth. Also, assuming the selection of operational items from this field test pool addresses concerns voiced by the external validation panel, they agreed that PISA 2012 will assess the construct of mathematical literacy as defined in the framework" (OECD, 2014,p.57).

On September 2011 mathematics experts met in Melbourne, Australia to review all material and recommended items to be included in the main survey instruments. The experts were guided by recommendations from National Centre feedback. For example, items given high priority ratings by National Centers were to be preferred, substantive quality of each item like the psychometric properties of all selected items had to be satisfactory, the ability of each item to fit to framework, for instance, items that generated coding problems in the field trial were avoided, and range of difficulty of each item was considered. For example, “appropriate distribution of item difficulties, broad enough to generate useful measurement data at both extremes of the anticipated ability distribution of sampled students across all participating countries." (OECD, 2014, p.243). The final survey instrument (mathematics assessment) was dispatched to various national centers between September 2, 2011, and December 20, 2011.

The assessment consisted of 85 mathematics items, 44 reading items 40 financial literacy, and 53 science items. Each student was randomly given one of the 13 assessment booklets which comprised of four clusters allocated according to a rotated test design among the seven mathematical literacy clusters, three scientific literacy clusters, and three reading literacy clusters. There were at least two mathematical literacy clusters in each booklet. Reading and science clusters only appeared in some of the booklets. The average number of items per cluster was 12 items for mathematics, 15 items for reading, 18 items for science, and 20 items for financial literacy. Each cluster was designed to average 30 minutes of test material. Total testing time was 2 hours. (OECD, 2014).

> Approximately half of the items were multiple-choice, about 20 percent were closed or short response types (for which students wrote an answer that was

simply either correct or incorrect), and about 30 percent were open constructed responses (for which students wrote answers that were graded by trained scorers using an international scoring guide). In PISA 2012, every student answered mathematics items. Not all students answered reading, science items, and/or financial literacy items (OECD, 2014, p.41).

In Australia, the PISA assessments took place in a six-week period from late July to early September 2012. The assessments were administered by sampled staff who were trained in accordance with PISA procedures. PISA quality monitors (PQM) were engaged to oversee the administration of the assessment. On average, two or three PQM were present in each participating school. Each education system was responsible for the collection of its data.

Cognitive activation in mathematics lessons. The cognitive activation in mathematics lessons instrument surveyed students on the teaching styles of their teachers. The leading statement on the cognitive activation in mathematics lessons instrument was “Thinking about the mathematics teacher that taught your last mathematics class." How often does each of the following happen?" Additionally, students responded to the following statements like: “The teacher presents problems that require students to apply what they have learned to new contexts” and “The teacher presents problems in different contexts so that students know whether they have understood the concepts.” In total students responded to nine statements in this variable. Students had four options to choose from: 1 for strongly agree, 2 for agree, 3 for disagree and 4 for strongly disagree. A high score indicated strong disagreement with the construct statements. There are no negatively worded statements on the survey.

Instrumental motivation to learn mathematics. The instrumental motivation to learn mathematics instrument sought students' views on the benefits of pursuing mathematics and mathematics-oriented courses. The introductory statement on this instrument was, "Thinking about your views on mathematics, to what extent do you agree with the following statements?” Examples of statements in the instrumental motivation to learn mathematics instrument are “Mathematics is an important subject for me because I need it for what I want to study later on” and “Learning mathematics is worthwhile for me because it will improve my career prospects or chances.” Participants responded by indicating their agreement or disagreement with each of the statements on a four-point scale, 1 for strongly agree, 2 for agree, 3 for disagree and 4 for strongly disagree. A high score indicated strong disagreement with the construct statements. There are four statements in the instrumental motivation to learn mathematics instrument, and none are negatively worded.

Mathematics anxiety. The mathematics anxiety instrument surveyed students on the negative thoughts (feeling of tension, nervousness and/or worrying about failure) they experience whenever they think about mathematics. The prelude of the instrument is, “Thinking about studying mathematics, to what extent do you agree with the following statements?" Participants replied to five statements. All statements were negatively worded. Examples of statements in mathematics anxiety instrument are, “I often worry that it will be difficult for me in mathematics classes” and “I get very tense when I have to do mathematics homework.” Participants responded by indicating their agreement or disagreement with each of the statements on a scale of four points. The scale of the instrument coded as: 1 for strongly agree, 2 for agree, 3 for disagree and 4 for strongly disagree. A high score indicated strong disagreement with the construct statements.

Mathematics work ethic. The survey statements in the mathematics work ethic instrument were geared towards soliciting students' views of their mathematics study habits. The leading statement on this instrument was, "Thinking about the mathematics you do for school, to what extent do you agree with the following statements?" Examples of supplementary statements in the mathematics work ethics instrument were, "I avoid distractions when I am studying mathematics" and "I keep studying until I understand mathematics material." Participants responded by indicating their agreement or disagreement with each of the statements on a scale of four points. The scale of the instrument coded as: 1 for strongly agree, 2 for agree, 3 for disagree and 4 for strongly disagree. A high score indicated strong disagreement with the construct statements. There are nine statements in the instrumental motivation for learning mathematics instrument, and none are negatively worded.

Relations between four latent variables (cognitive activation in mathematics lessons, mathematics anxiety, instrumental motivation to learn mathematics and mathematics work ethic) were investigated in this study. A complete list of all latent variables used in this study and associated statements are in appendix A.

Gender. Students disclosed their sexual orientation by choosing from two options, 1 for female and 2 for male.

Index of economic, social and cultural status (ESCS). The ESCS was based on three indices: the highest occupational status of parents (HISEI); the highest educational level of parents in years of education (PARED); and home possessions (HOMEPOS).

The index of home possessions (HOMEPOS) comprises all items on the indices of family wealth (WEALTH), cultural resources (CULTPOSS), access to home educational and cultural resources (HEDRES), and books in the home. (OECD, 2014, pg.270).

Data used in the construction of this index was obtained from parents via questionnaire. Official records in school possessions were used to complement missing data. Where two out of three indices were missing, ESCS status for that student was not calculated. “The ESCS scores were obtained as component scores for the first principal component with zero being the score of an average OECD student and one being the standard deviation across equally weighted OECD countries," (OECD, 2014, p.270).

Mathematics and scientific literacy. Procedures for administrating, reporting and interpretation of mathematics and scientific literacy assessment scores are identical. Students were assessed in mathematics and scientific concepts which were organized in domain.

> In PISA 2012, there are six levels of mathematical and scientific literacy proficiency. For each of the literacy domains, a mean score across OECD countries has been defined: 504 score points with a standard deviation of 92 for mathematical literacy; 501 score points with a standard deviation of 93 for scientific literacy” (OECD, 2014, p. 10).

Missing data were imputed. Mathematics literacy sample questions for PISA 2012 are in appendix B.

Missing Data

Missing data mean that one or more observation(s) expected in a dataset has a null value (Gemici et al., 2014). Gemici, Bednarz, & Lim added that the missing values could be the independent variables, dependent variable or both variables. Some of the reason why values may be missing in a dataset are: a participant drops from the study, a participant refuses to respond to the whole survey or parts of a survey (especially where the survey is asking for personal information like participants income or history with drug abuse), participants fatigue because of complicated and lengthy questionnaires which discourage, participants' lack of interest in the survey among others (Gemici et al., 2014; Hoevenaar-Blom et al., 2017; Paiva & Reiter, 2015). However, there are cases when the missing data is intentional or planned. Huge cost of data collection, logistical challenges in harmonizing participants' schedules, for example, surveying students in different countries and education systems, are some of the factors which influence planned missing values approach in data collection (Coertjens, Donche, De Maeyer, Vanthournout, & Van Petegem, 2017; Paiva & Reiter, 2015; Wu & West, 2010).

Missing not at random (MNAR), missing at random (MAR) and, missing completely at random (MCAR) among others are categories of missing data (Gemici et al., 2014; Hoevenaar-Blom et al., 2017; Paiva & Reiter, 2015). First, missing not at random (MNAR) also known as non-ignorable nonresponse refers to unknown situation or process in the data which discourages participants from responding to the question(s) on the survey (Coertjens et al., 2017; Hoevenaar-Blom et al., 2017; Manly & Wells, 2015). For example, survey participants may not self-report on deviant behavior (lying on a test or low grades) accurately. Therefore, it is safe to assume that missing value or lower levels responses represent higher levels of deviant behavior. Pattern mixture (PM) and selection models are used to handle MNAR (Coertjens et al., 2017).

Second, missing at random (MAR) refer to missingness which can be explained if complete information is available or when the missing observations are linked to one or more of the other variables in the dataset (Coertjens et al., 2017; Gemici et al., 2014; Hoevenaar-Blom et al., 2017) . For example, in a semester where students are required to take several tests, if few students miss one or two test at random, their scores on the missed tests can be imputed from the two tests they took. MAR occurs frequently and there are several remedial measures used for handle MAR, like maximum likelihood (ML), multiple imputations (MI), maximum likelihood with auxiliary variables (MLaux), and multiple imputation with auxiliary variables (MIaux) are some of the methods used to handle MAR (Coertjens et al., 2017; Gemici et al., 2014; Hoevenaar-Blom et al., 2017 & Manly & Wells, 2015) . The Program for International Student Assessment **(**PISA**)** use these imputation methods to handle missing observations.

Third, missing completely at random (MCAR) refers to missing observation which is not associated with observed data (Coertjens et al., 2017; Manly & Wells, 2015). For example, survey participants who decide to abandon the exercise after responding to few statements. Listwise deletion (LD) is one of the recommended ways of handling MCAR (Gemici et al., 2014).

Although missing data pose challenges like increasing the likelihood of biased results, reduction of sample size, and limited generality of study results, careful application of remedial measures increase sample size and widen the number of analysis which can be performed on a large dataset.

Data Analysis

Statistical Package for the Social Sciences (SPSS) software and Microsoft Office (Excel) were used for data analysis. The following pre-analyses were done on the data before comprehensive data analysis commences.

In the preliminary stages of data analysis, descriptive statistics (i.e., mean, standard deviation) were calculated for each continuous variable. Similarly, data descriptive statistics function in statistical package for the social sciences (SPSS) was used to detect missing data and outlier. The normality of the variables were examined using the normal distribution techniques. Also, the following assumptions were examined: linearity, collinearity, normality, and homoscedasticity.

The relations among the study variables were explored using SEM (Analysis of Moment Structure [AMOS]) version 25 software with the maximum likelihood estimation method. Its ability to explore the relationship among variables simultaneously and the capability to estimate the error of each variable independently informed the selection of SEM over logit and regression analysis. Furthermore, SEM's flexibility allows for the construction of statistical models and testing these against predetermined parameters to check the fitness of the model (Duckworth & Kern, 2011). These features are not available in regression analysis. For this study, the SEM model was comprised of two integrated analyses: confirmatory factor analysis and path analysis.

Confirmatory factor analysis is a subsection of the structural equation model (SEM). This method was used to assess the discriminant and convergent validity of each survey statement for the study variables (Carlson & Herdman, 2012; Duckworth & Kern, 2011; Raykov, 2011). For example, to assess convergent validity, the composite reliability and average variance extracted from each variable were examined. Additionally, the factors loading of each statement were calculated. Discriminant validity, the inter-construct correlations and the square root of the average variance extracted were examined. Discriminant validity "assesses the degree to which the constructs are empirically different" (Raykov, 2011, p.19).

All variables were included in the construction of the study model in SEM. The SEM model fitness indices were compared against recommended model fit indices. The following comparative indices were used to assess the fitness of the model compared to an alternative baseline model (Duckworth & Kern, 2011). Examples of comparative indices are the Comparative Fit Index (CFI) and the Tucker-Lewis index (TLI). CFI and TLI values above 0.90 indicate an acceptable fit to the data (Levy, 2011). Likewise, the parsimony indices compare the complexity of two models, and the simpler model (the model with the fewest free parameters) is selected, assuming all other factors are constant (Iacobucci, 2010; Olivares & Forero, 2010; Ravallion, 2012). An example of a parsimony index is the root mean square error of approximation (RMSEA). RMSEA values below 0.05 indicate good approximations to the data (Levy, 2011). Third, an absolute fit index evaluates how well the proposed model reproduces the observed data (Henseler & Sarstedt, 2013; Park & Hill, 2016; Wu & West, 2010). Examples of absolute fit indices include the chi-square and root mean square residual (SRMR). SRMR value below 0.08 is recommended (Levy).

Path analysis is a subset of structural equation model (SEM) which is used to evaluate the relations between two or more independent variables and an independent variable in a causal model. Furthermore, path analysis was used to examine direct and indirect causal effects between independent and dependent variables. Therefore, path analysis was used to estimate the following paths:

1. Cognitive activation in mathematics lessons to instrumental motivation to learn mathematics to mathematical literacy and scientific literacy performance.

2. Cognitive activation in mathematics lessons to mathematics anxiety to mathematical literacy and scientific literacy performance.

3. Cognitive activation in mathematics lessons to instrumental motivation to learn mathematics to mathematics work ethic to mathematical literacy and scientific literacy performance.

4. Cognitive activation in mathematics lessons to mathematics anxiety to mathematics work ethic to mathematical literacy and scientific literacy performance.

Mediation effect between cognitive activation in mathematics lessons (independent variable) and mathematical literacy and scientific literacy performance (dependent variables). After estimating the full model, I ran subsequent tests to isolate aspects of the full model to test each hypothesis related to mediation. Separate analyses were run for each mediational hypothesis. In conducting these subsequent tests, I only estimated the paths involving the mediational hypothesis and constrained other relationships among variables in the model to zero. Bootstrapping in AMOS was used in examining the mediation effects of each path. The distribution of the standard errors were not normally distributed. Therefore, bootstrap was used to correct for the non-normality of the standard errors (Preacher and Hayes, 2008). Mathematics anxiety, instrumental motivation to learn mathematics and mathematics work ethic were mediator variables in this study. Four hypothesis were tested for mediation using paths mentioned in the path analysis section.

The multi-group SEM model testing was done to establish the invariance of students' socioeconomic status and gender. Each path in the four hypotheses was tested for moderation. Paths outside the hypothesis of interest were set to a regression weight of zero. For example, when testing for moderation for the first hypothesis, paths in hypotheses two to four were set to a regression weight of zero. In total 28 paths (14 paths by gender and 14 paths by socioeconomic status) were tested for moderation.

Limitations of the Data Analysis

Primarily, PISA assessments were meant for comparison of education systems among participating countries as opposed to specific educational needs of a particular country (OECD, 2014). Therefore, the findings of this study may not form the basis of initiating wide-reaching education reforms in participating countries (Australia), although this study's findings offer valuable lessons on the state the Australian education system. Education reforms should be informed by assessments which are closely linked to the curriculum in each country or state (OECD).

PISA assessments rely on rotated student context questionnaires to assess motivational and affective factors, rotation cognitive skills test and data imputation to cover wide content and population at a relatively low cost, and there are discrepancies between imputed and actual data (Wu, 2002). According to Wu, plausible values should not substitute the actual results. Therefore, precaution should be taken when making key decisions based on the findings of this study.

Review of Research Question and Hypotheses

This study examined the effects of motivational and affective factors on students' performance in mathematical literacy and scientific literacy. Specifically, the study investigated the mediational role of instrumental motivation to learn mathematics, anxiety for mathematics and, mathematics work ethic in the relationship between cognitive activation in mathematical literacy and scientific literacy performance among Australian students. Also, this study will explore if these relationships are invariant based on socioeconomic status (SES) and gender.

Research Question 1.

Do students' instrumental motivation, anxiety, and work ethic for mathematics mediate relationships between cognitive-activation instruction and students' PISA test scores in mathematical literacy and scientific literacy?

Hypothesis 1a. Cognitive-activation instruction will positively predict students' instrumental motivation for mathematics which will positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Hypothesis 1b. Cognitive-activation instruction will negatively predict students' anxiety for mathematics which will negatively predict students' PISA tests scores in mathematics and science.

Hypothesis 1c. Cognitive-activation instruction will positively predict students' instrumental motivation for mathematics which will positively predict students' mathematics work ethic which will, in turn, positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Hypothesis 1d. Cognitive-activation instruction will negatively predict students' anxiety for mathematics which will negatively predict students' mathematics work ethic which will, in turn, positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

Research Question 2.

Does students' gender and/or parental income moderate any of the mediational paths proposed under Research Question 1?

Hypothesis

Hypothesis 2a. One or more of the mediational paths proposed under research Question 1 will be moderated by gender.

Hypothesis 2b. One or more of the mediational paths proposed under research Question 1 will be moderated by students' family income.

Variable names, data type, type of the variable and the role of each variable in the study model are summarized below (see Table 4). All variables were analyzed in chapter 4.

Table 4

List of Variables and their Use

Variable name	Data Type	PISA Report Year	Type of Variable	Role in Model
Cognitive Activation in mathematics lesson	Ordinal	2012	Independent	Exogenous
Mathematics anxiety	Ordinal	2012	Independent/Mediator	Endogenous
Motivation to learn mathematics	Ordinal	2012	Independent/Mediator	Endogenous
Students' mathematics work ethic	Ordinal	2012	Independent/Mediator	Endogenous
Mathematics performance	Interval/continuous	2012	Dependent	Endogenous
Science performance	Interval/continuous	2012	Dependent	Endogenous
Gender	Nominal/Categorical	2012	Moderator	
Student's socioeconomic status	Nominal/Categorical	2012	Moderator	

Chapter III Summary

Chapter three discussed the study's design, sampling procedure, and the study sample size. Likewise, the derivation of the study instruments and validity was explained in this chapter. The administration of the study surveys and data collections procedures were expounded. Additionally, how to identify missing data and the imputation procedures for missing data, data cleaning produce and data analysis techniques to be used in this study were discussed. Limitations of the data analysis were also mentioned. Finally, a review of the study questions hypothesizes and rational was discussed.

IV: RESULTS

Data Analysis and Results

In this chapter preliminary and primary data analyses of this study were conducted and interpreted. The preliminary analyses section focused on data cleaning, imputation of missing data, calculation of descriptive statistics and psychometric properties of the study variables and testing of assumptions. For example, the normality of the data, multicollinearity, and adequacy test. Primary data analyses section focused on model building, verifying the fitness of the study model, and testing hypotheses.

The original data contained over 14000 students records and over 60 columns. Data for this study were obtained by deleting the extra entries from the original dataset. After deleting extra columns from the dataset, 4500 students' records (rows) which had competed and valid data, entries were randomly selected to form the sample size for this study.

Data Cleaning and Missing Data Procedure

To ensure accuracy of the study results, data were screened before statistical analyses were conducted. Survey items for cognitive activation in mathematics lessons, instrumental motivation to learn mathematics, mathematics anxiety and mathematics work ethic variables were reversed coded to ensure correct interpretation of each variable. For example, after reverse coding each item, higher scores on anxiety indicated higher anxiety and higher scores on work ethic indicated higher work ethic. There were no missing values or outliers in the selected sample size used in this study because incomplete and invalid students’ records were deleted.

Descriptive Statistics

Descriptive statistics were calculated to provide a comprehensive overview of the data sample. The following values were calculated for each survey item: mean, standard deviation, skewness, and kurtosis (see Tables 5). The mean values of the survey items comprising the study's cognitive and affective latent constructs (i.e., cognitive activation in mathematics lessons, instrumental motivation to learn mathematics, mathematics anxiety, and mathematics work ethic) ranged from 2.13 to 3.08. The lowest value on each survey scale was one and the maximum value was four. Likewise, the standard deviation values ranged from 0.66 to 0.93. Skewness values fluctuated from -0.60 to 0.15. Skewness values of |0.5| are symmetric, |0.5-1.0| are slightly skewed and absolute values ≥ 1.0 are skewed.

Kurtosis values fluctuated between - 0.82 and 1.20. Skewness and kurtosis values demonstrated that, data distribution in the survey items comprising the latent constructs were approximately symmetric (Field, 2013). These results revealed that the data sample were univariate normal. Tables 5 contain descriptive summary of independent and mediator variables.

Table 5

Descriptive Summary of Study Independent and Mediator Variables

Latent variable	Indicators	Mean	Std. Deviations	Skewness	Kurtosis
Cognitive activation in mathematics lessons	Cognitive1R	2.79	0.91	-0.23	-0.81
	Cognitive2R	2.83	0.86	-0.27	-0.70
	Cognitive3R	2.34	0.93	0.21	-0.82
	Cognitive4R	2.63	0.89	-0.06	-0.77
	Cognitive5R	2.88	0.90	-0.36	-0.72
	Cognitive6R	3.00	0.93	-0.53	-0.71
	Cognitive7R	2.96	0.92	-0.47	-0.71
	Cognitive8R	3.00	0.86	-0.44	-0.64
	Cognitive9R	2.78	0.89	-0.18	-0.80
Instrumental motivation for mathematics	Instrumental1R	3.04	0.77	-0.64	0.29
	Instrumental2R	3.07	0.77	-0.78	0.63
	Instrumental3R	2.90	0.88	-0.49	-0.43
	Instrumental4R	3.00	0.81	-0.63	0.10
Mathematics anxiety	Anxiety1R	2.70	0.80	-0.13	-0.46
	Anxiety2R	2.37	0.83	0.31	-0.42
	Anxiety3R	2.24	0.76	0.49	0.12
	Anxiety4R	2.13	0.79	0.58	0.19
	Anxiety5R	2.75	0.90	-0.27	-0.72
Mathematics work ethic	Ethics1R	2.77	0.82	-0.28	-0.41
	Ethics2R	2.68	0.81	-0.12	-0.49
	Ethics3R	2.75	0.78	-0.25	-0.30
	Ethics4R	2.53	0.79	0.15	-0.46
	Ethics5R	2.67	0.80	-0.06	-0.49
	Ethics6R	3.08	0.69	-0.56	0.76
	Ethics7R	3.08	0.66	-0.63	1.20
	Ethics8R	2.59	0.77	0.13	-0.46
	Ethics9R	2.77	0.79	-0.24	-0.37

Note. *N* (sample size) = 4500, Lowest value =1, Maximum value = 4

The means of the dependent variables (plausible values in mathematics and science) ranged from 497.06 to 517.60. Standard deviation of the dependent variables ranged from 94.68 to 100.10. Skewness values fluctuated from -0.16 to 0.01 which implies symmetric distribution of the data. Kurtosis values fluctuated between - 0.24 and -0.11. Tables 6 contain descriptive summary of dependent variables.

Table 6

Descriptive Summary of Study Dependent Variables

Dependent	Indicators	Mean	Std. Deviation	Skewness	Kurtosis
Plausible values (mathematics)	PVmath1	497.06	94.68	0.05	-0.22
	PVmath2	497.73	94.80	0.04	-0.15
	PVmath3	497.50	94.73	0.01	-0.20
	PVmath4	498.16	94.94	0.05	-0.20
	PVmath5	497.84	95.05	0.03	-0.24
Plausible values (Science)	PVscience1	516.38	99.46	-0.15	-0.11
	PVscience2	516.80	99.99	-0.14	-0.11
	PVscience3	517.21	99.57	-0.13	-0.15
	PVscience4	517.25	99.51	-0.12	-0.21
	PVscience5	517.60	100.10	-0.16	-0.14

Notes. N (sample size) = 4500, plausible values have a mean of approximately 500 and a standard deviation of approximately 100 across OECD countries (OECD, 2014).

The moderator variables were gender and socioeconomic status. The sample size was 4500 students, girls were 2222 (49.4%), and boys were 2278 (50.6%). Australian students' mean score in mathematics was 498. Australian students' mean score in science was 517. In the Australian data, boys displayed a higher mean score in mathematics (*m* = 506) compared to girls (*m* = 489). Boys outperformed girls by 17 points on average in mathematics. Likewise, boys had a higher mean score in science (*m* = 521) compared to girls (513). Boys outperformed girls by 8 points on average in science. Table 7 presented a summary of the study sample, percentages of girls and boys in the Australia PISA 2012 dataset, and their mean mathematics and science scores.

Table 7

Mathematics and Science Mean Scores (Based on Students' Gender)

Gender	N (%)	mean math score	S.D	mean science score	S.D
Girls	2222 (49.4%)	489	90	513	95
Boys	2278 (50.6%)	506	94	521	98
Total	4500(100%)	498	92	517	96

This study sample was also described using students' socioeconomic status (SES). There were 1747 (39%) low SES students and 2753 (61%) high SES students. High SES students displayed a higher mean score in mathematics (*m* = 521) compared to low SES students (*m* = 461). High SES students outperformed low SES students by 60 points on average in mathematics. Likewise, High SES students had a higher mean score in science (*m* = 541) compared to low SES students (*m* = 479). High SES students outperformed low SES students by 62 points on average in science. Table 8 presented a summary of the study sample, percentages of low SES students and High SES students in the Australia PISA 2012 dataset, and their mean mathematics and science scores.

Table 8

Mathematics and Science Mean Scores (Based on Students' Socioeconomic Status (SES))

SES	N (%)	mean math score	S.D	mean science score	S.D
Low	1747 (39%)	461	86	479	92
High	2753 (61%)	521	89	541	91
Total	4500(100%)	498	92	517	96

Correlation matrix examined the relation between each variable with other variables. A correlation coefficient of a variable with itself is 1, which appear on the diagonal of the correlation matrix. A positive correlation coefficient indicates that increases in one variable correspond with an increase in the other and vice versa. Second, correlations are used to check for bivariate multicollinearity. A Pearson correlation coefficient ≥ |0.85| indicates bivariate multicollinearity (Parkhurst et al., 2011). There were no bivariate multicollinearity among the independent and mediator variables. However, mathematics and science performance (dependent variables) correlation coefficient was 0.92. This coefficient shows that mathematics and science performance are closely related. The summaries of the construct correlation coefficient are in Table 9.

Table 9

Correlations Between all Study Variables

		1	2	3	4	5	6	7	8
1	Cognitive activation	1							
2	Instrumental motivation	0.28**	1						
3	Mathematics anxiety	-0.15**	-0.27**	1					
4	Mathematic work ethics	0.33**	0.51**	-0.32**	1				
5	Gender (Girls =0, Boys =1)	0.09**	0.13**	-0.19**	-0.01	1			
6	ESCS (Low =0, High =1)	0.10**	0.03	-0.11**	0.12**	0.49**	1		
7	Mathematics Performance	0.15**	0.21**	-0.39**	0.25**	0.10**	0.32**	1	
8	Science Performance	0.11**	0.14**	-0.31**	0.18*	0.04**	0.32**	0.92**	1

Note. N = 4500. ***p* < 0.01, * *p* < 0.05. ESCS: Economic, Social and Cultural Status.

Exploratory Factor Analysis (EFA)

The following preliminary analyses were done on the data sample before the Structural equation model (SEM) was constructed. The preliminary analysis were intended to evaluate the suitability of the data sample for the constructions of the study model. First, The Kaiser-Meyer-Olkin (KMO) was conducted to assess the adequacy of the study sample for factor analysis purposes. Second, extraction communalities were done on each variable to assess how each indicator was loading on the associated variable. Third, composite and discriminant reliability checks were performed on the sample data. Results and interpretations of all checks are explained in the next paragraph.

The Kaiser-Meyer-Olkin (KMO) statistic measures proportion of variance among variables. This test investigates the appropriateness of sample data to be used for factor analysis. A KMO value between 0.80-1.00 indicates the sampling is adequate for factor analysis. KMO measure of sampling adequacy test was 0.925, $p < 0.001$. The maximum likelihood method was used to calculate extraction communalities. Extraction values $\leq$ 0.4 indicate low variance is accounted for in each factor and they should be omitted in future analysis. Cognitive3 and cognitive4 had extraction communalities values < 0.45. Cognitive3 and cognitive4 were omitted from further analysis. The total variances explained was 60% for four factors. Likewise, the elbow of the scree plot was between factors 4 and 5.

The 27 items in four variables were tested for convergent validity by determining factor loadings, composite reliability and average variance extracted (AVE). According to Fornell & Larcker (1981), the minimum requirement suggested for item loadings is .7, composite reliability is .7 and AVE is 0.5. Average variance extracted = $(\sum\lambda^2)$/n, n is the number of factors in each variable. Composite reliability = $\frac{(\sum\lambda)^2}{(\sum\lambda)^2+\sum e}$, e =1-λ^2. The item loadings, composite reliability and the average variance extracted are reported in Table 10.

Table 10

Indicators Loading, Average Variable Extracted, Composite Reliability, and Communalities

Latent variable	Indicators	Factor Loading (λ)	Average variance extracted (AVE)	Composite Reliability (CR)	Communalities
Cognitive activation in mathematics lessons	Cognitive1	0.73	0.50(0.52)	0.90(0.88)	0.55
	Cognitive2	0.73			0.52
	Cognitive3	0.66			0.42
	Cognitive4	0.64			0.37
	Cognitive5	0.75			0.56
	Cognitive6	0.68			0.52
	Cognitive7	0.70			0.49
	Cognitive8	0.75			0.57
	Cognitive9	0.72			0.51
Instrumental motivation for mathematics	Instrumental1	0.86	0.78	0.93	0.78
	Instrumental2	0.88			0.80
	Instrumental3	0.91			0.78
	Instrumental4	0.88			0.78
Anxiety for mathematics	Anxiety1	0.82	0.63	0.89	0.65
	Anxiety2	0.79			0.67
	Anxiety3	0.85			0.69
	Anxiety4	0.72			0.59
	Anxiety5	0.77			0.56
Mathematics work ethic	Ethics1	0.77	0.59	0.93	0.58
	Ethics2	0.84			0.67
	Ethics3	0.68			0.60
	Ethics4	0.80			0.61
	Ethics5	0.73			0.61
	Ethics6	0.79			0.61
	Ethics7	0.76			0.60
	Ethics8	0.77			0.55
	Ethics9	0.75			0.54

Notes. Numbers in parenthesis in 4th and 5th columns represent Average variance extracted (AVE) and Composite Reliability (CR) value in cognitive activation in mathematics lessons factor before Cognitive3 and Cognitive4 were deleted. Screen shots of indicators loading and communalities before cognitive3 and cognitive 4 were deleted are in appendix C.1 and C.2 respectively.

Results indicate that all item loadings were above the recommended cut-off point, except cognitive3 and cognitive4 and ethic3. After omitting cognitive3 and cognitive4, composite reliability (CR) decreased from 0.90 to 0.88. The extraction communalities of the remaining items were above 0.4, indicating that all items fit well with the other items in the factors.

Composite reliability was obtained for each construct, and the results show that all four constructs met the suggested minimum value of .7. The final criterion to satisfy convergent validity was the measure of the Average Variance Extracted (AVE) for each factor. After omitting cognitive3 and cognitive4 AVE improved from 0.50 to 0.52 for the cognitive activation factor. The AVE values of the other factors (Instrumental motivation to learn mathematics, mathematics anxiety and mathematics work ethic) were 0.78, 0.63 and 0.59 respectively. These results indicated that the items in each construct were highly correlated and reliable. Therefore, the measurement properties satisfied necessary criteria of convergent validity.

Discriminant validity was measured by taking the square root of AVE for each construct. If the square root of AVE is larger than the inter-construct correlation, then discriminant validity is achieved. The discriminant validity provided evidence that the constructs were measuring different parts of the overall construct. Table 11 displays the square root of the AVE for each construct and the correlations among other constructs.

Table 11

Inter-Construct Correlations and Square Root of Average Variance Extracted

Constructs	Motivation	Anxiety	Ethic	Cognitive
Motivation	**(0.84)**			
Anxiety	-0.27**	**(0.75)**		
Ethic	0.51**	-0.32**	**(0.73)**	
Cognitive	0.28**	-0.15**	0.33**	**(0.69)**

******p<0.01 numbers in bold and parentheses in the diagonal are square roots of average variance extracted.

Measurement Model. After cognitive3 and cognitive 4 were deleted the indicator loading on each factor improved. All indicators were above the recommended cut-off of 0.7 except ethic3 = 0.68. Likewise, all extraction communalities exceeded recommended cut-off of 0.4. This test was performed to increase the fitness of the data in the structural equation model. Table 12 contains indicators loading after cognitive3 and cognitive 4 were deleted.

Table 12

Indicators Loading after Cognitive3 and Cognitive4 were Deleted

Latent variable	Indicators	1	2	3	4	Communalities
Cognitive activation in mathematics lessons	Cognitive1	0.75				0.57
	Cognitive2	0.71				0.49
	Cognitive5	0.77				0.60
	Cognitive6	0.73				0.57
	Cognitive7	0.74				0.53
	Cognitive8	0.78				0.61
	Cognitive9	0.72				0.51
Instrumental motivation for mathematics	Instrumental1		0.86			0.78
	Instrumental2		0.88			0.80
	Instrumental3		0.91			0.78
	Instrumental4		0.89			0.78
Anxiety for mathematics	Anxiety1			0.82		0.65
	Anxiety2			0.79		0.67
	Anxiety3			0.85		0.69
	Anxiety4			0.72		0.59
	Anxiety5			0.77		0.56
Mathematics work ethic	Ethics1				0.78	0.58
	Ethics2				0.84	0.67
	Ethics3				0.68	0.60
	Ethics4				0.80	0.61
	Ethics5				0.73	0.61
	Ethics6				0.78	0.61
	Ethics7				0.76	0.60
	Ethics8				0.77	0.55
	Ethics9				0.75	0.54

Note. Screen shots of indicators loading and communalities after cognitive3 and cognitive 4 were deleted are in appendix C.3 and C.4 respectively.

Confirmatory Factor Analysis (CFA)

The purpose of this analysis was to investigate data fitness of each variable before it was used in the construction of an inclusive model (including all variables). If data sample does not fit the variable adequately, remedial measures are taken. Four models were constructed (one for each latent variables). Cognitive activation in mathematics lesson, instrumental motivation to learn mathematics, mathematics anxiety and students' mathematics work ethic were the four factors. Indicators were loaded on each factor and their results were compared with the recommended model fix indices. The recommended model fit indices are Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) ≥ 0.9 and Root Mean Square Error of Approximation (RMSEA) ≤ 0.05 (Kline, 2010). All variables in this study met these recommendations. Relations between each latent variable and its indicators were calculated and summarized in Table 13.

Table 13

Model Fit Summaries of Latent Variables

Latent variables	Number of Indicators	x^2	x^2/df	P	TLI	CFI	RMSEA	LO	HI
Cognitive	7	151.64	11.67	0.00	0.98	0.99	0.05	0.04	0.06
Motivation	4	5.52	5.52	0.02	1.00	1.00	0.03	0.01	0.06
Anxiety	5	19.36	6.45	0.00	0.99	1.00	0.04	0.02	0.05
Work ethic	9	809.28	33.72	0.00	0.95	0.97	0.09	0.08	0.10

Notes. RMSEA Confidence, 90%. Lower (LO) and Upper/High (HI) bounds.

Structural Equation Modelling (SEM)

Structural equation modeling (SEM) was used in this study. This method was appropriate for several reasons. First, SEM is "flexible" compared to linear regression because it allows calculation of regression weights from one variable to other variables simultaneously. A method with this capability was necessary for this study because the independent and each mediator variables regressed to at least two variables (Khine, Al-Mutawah, & Afari, 2015). Second, SEM allows for the modeling and testing of complex patterns and multitude hypothesis in a relation simultaneously (Preacher & Merkle, 2012). Third, SEM takes measurement errors into account, therefore minimizing the effects of a likelihood of biased relations between variable (Streukens & Leroi-Werelds, 2016). There are two major components to the model, the measurement model, and the path model.

Analysis of a moment structures (AMOS) 25.0 was used to construct the measurement model and test hypothesized path model. The maximum likelihood, the default estimation method was used to generate path estimates. Tables 10 summarized the commonly used measures of measurement model fit based on results from an analysis of the structural model, the recommended level of acceptable fit, and the fit indices for the research model in this study. There were small discrepancies between model fit based on results from an analysis of the structural model and the recommended estimates. The chi-square ($\chi 2$) was significant. According to Khine, Al-Mutawah, & Afari (2015), as the sample size increases, there is a tendency for the $\chi 2$ to indicate significant differences. The results of the model fit, as shown by the various fit indices in Table 14, indicate that the research model fits the data was reasonably good fit. Figure 2 displayed standardized regression estimates and the factor loadings of each item on its respective latent factor on each path of the study model.

Table 14

Fit Indices for the Research Model (All Variables)

Model Fit Indices	Value	Recommended Guidelines	References
x^2(Chi-Square)	21569.987 $p < 0.000$	Nonsignificant	Kline (2010); McDonald & Ho (2002)
x^2/df	39.351	< 5	Kline (2010); McDonald & Ho (2002)
TLI	0.856	≥ 0.90	McDonald & Ho (2002)
CFI	0.867	≥ 0.90	Byrne (2010); McDonald & Ho (2002)
RMSEA	0.092	< 0.05	McDonald & Ho (2002)

Note: TLI: Tucker-Lewis Index, CFI: Comparative Fit Index, RMSEA: Root Mean Square Error of Approximation. The RMSEA Confidence = 90%, Lower Bound = 0.091 and Upper Bound = 0.093.

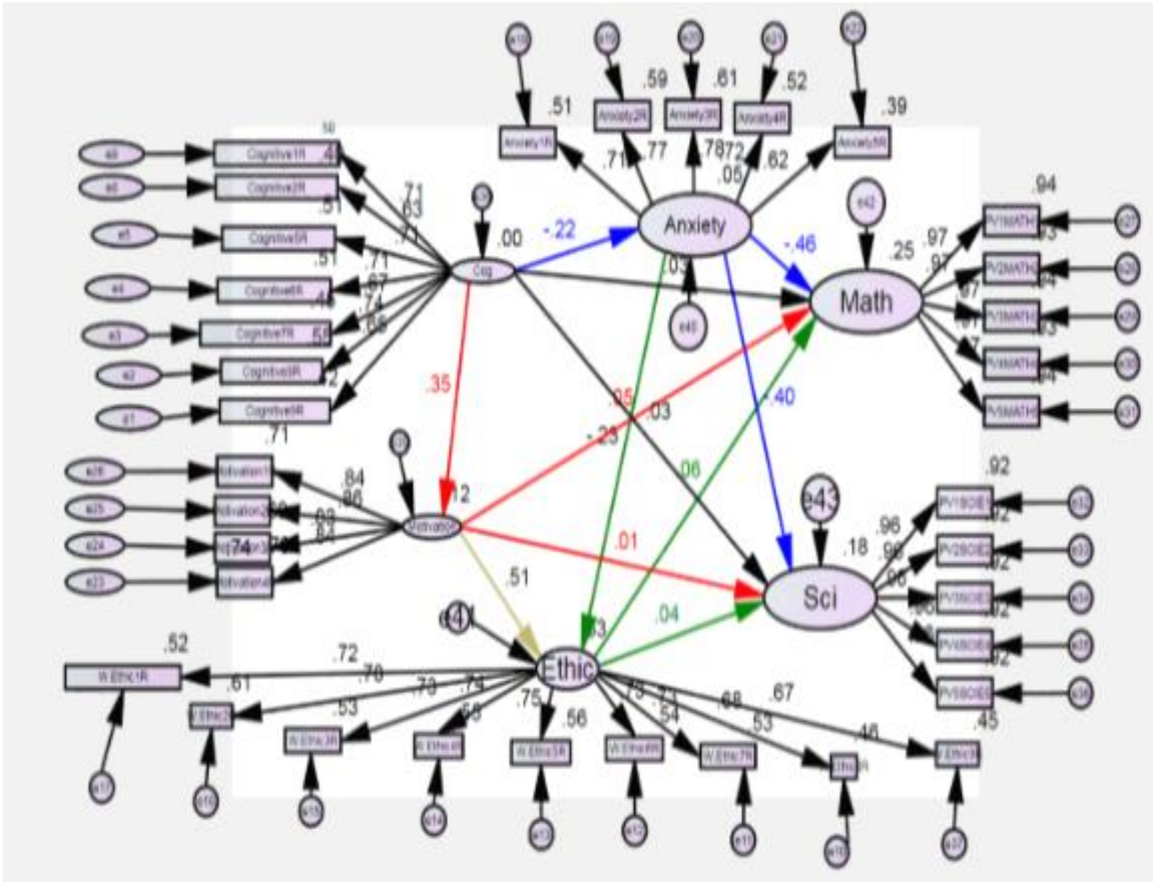


Figure 2: Screenshot of the Full SEM Model

Path Model. Relations in the structural model were interpreted as the effect of a latent variable on each other. According to Kline (2010), the effect sizes with values 0.5 or higher were considered large, those less than 0.3 were considered medium, and effect sizes values of 0.1 or less were considered small. In this section, the standardized regression weights of the whole model are discussed and interpreted.

Instrumental motivation to learn mathematics (β = 0.33, *SE* = 0.021, *p* < 0.001) was statistically significant and positively related to cognitive activation. This result says that given an increase in cognitive activation of one standard deviation, an increase of 0.35 standard deviation is expected in motivation to learn mathematics, controlling other variables in the model. This effect on instrumental motivation to learn mathematics (β =

0.33) suggest that, as students perceive positive medium cognitive activation in mathematics lessons, they are likely to be motivated to learn mathematics concepts so that they can apply them in future. Cognitive activation in mathematics explained approximately 12% of variations in motivation to learn mathematics. Instrumental motivation to learn mathematics (β = 0.20, SE = 2.228, $p < 0.001$) was statistically significant and positively related to mathematics performance. This result says that given an increase in motivation to learn mathematics of one standard deviation, an increase of 0.20 standard deviation is expected in mathematics performance, controlling other variables in the model. Furthermore, instrumental motivation to learn mathematics (β = 0.14, SE = 2.347, $p < 0.05$) was positively related to science performance and statistically significant. This result says that given an increase in motivation to learn mathematics of one standard deviation, an increase of 0.13 standard deviation is expected in science performance, controlling other variables in the model. These effects, instrumental motivation to learn mathematics (β = 0.20 and β = 0.14), suggests that students' instrumental motivation to learn mathematics had a small positive effect on their mathematics and science performance. Motivation to learn mathematics explained than 4% and 2% of the variations in mathematics and science performance respectively.

Mathematics anxiety (β = -0.20, SE = 0.017, $p < 0.001$) was statistically significant and negatively related to cognitive activation in mathematics. This result says that given an increase in cognitive activation of one standard deviation, a decrease of 0.20 standard deviation is expected in mathematics anxiety, controlling other variables in the model. This effect on mathematics anxiety (β = -0.20) suggests that, perceived negative medium cognitive activation in mathematics lessons is likely to lower mathematics anxiety among students. Cognitive activation in mathematics explained approximately 5% of variations in mathematics anxiety respectively. Mathematics anxiety (β = -0.49, SE = 2.684, p < 0.001) was statistically significant and negatively related to mathematics performance. This result says that given an increase in mathematics anxiety of one standard deviation, a decrease of 0.49 standard deviation is expected in mathematics performance, controlling other variables in the model. Likewise, mathematics anxiety (β = -0.42, SE = 2.807, p < 0.001) was statistically significant and negatively related to science performance. This result says that given an increase in mathematics anxiety of one standard deviation, a decrease of 0.42 standard deviation is expected in science performance, controlling other variables in the model. Mathematics anxiety had a medium negative effect (β = -0.49 and β = -0.42) on mathematics and science performance respectively. These effects suggest that, as students experience mathematics anxiety, they are unlikely to excel in mathematics and science performance. Mathematics anxiety accounted for 24% and 18% of variation in mathematics and science performance respectively.

Motivation to learn mathematics (β = 0.35, SE = 0.021, p < 0.001) was statistically significant and positively related to cognitive activation. This result says that given an increase in cognitive activation of one standard deviation, an increase of 0.35 standard deviation is expected in motivation to learn mathematics, controlling other variables in the model. This effect on motivation to learn mathematics (β = 0.35) suggest that, as students perceive positive medium cognitive activation in mathematics lessons, they are likely to be motivated to learn mathematics. Motivation to learn mathematics (β = 0.57, SE = 0.013, p < 0.001) was statistically significant and positively related to mathematics work ethic. This result says that given an increase in motivation to learn mathematics of one standard deviation, an increase of 0.57 standard deviation is expected in mathematics work ethic, controlling other variables in the model.

Motivation to learn mathematics had a large positive effect ($\beta = 0.51$) on mathematics work ethic. This effect suggests that, as students experience motivation to learn mathematics, they are likely to observe mathematics work ethic. Approximately 26% of variations in mathematics work ethic were explained by motivation to learn mathematics. Mathematics work ethic ($\beta = 0.25$, $SE = 2.792$, $p < 0.001$) was statistically significant and positively related to mathematics performance. This result says that given an increase in mathematics work ethic of one standard deviation, an increase of 0.25 standard deviation is expected in mathematics work ethic, controlling other variables in the model. Mathematics work ethic had a small positive effect ($\beta = 0.25$) on mathematics performance. This suggests that students' mathematics work ethic are likely to improve students' mathematics performance. Less than 7% of variations in mathematics performance was explained by mathematics work ethic.

Mathematics work ethic ($\beta = 0.19$, $SE = 2.919$, $p < 0.001$) was statistically significant but it was positively related to science performance. This result says that given an increase in mathematics work ethic of one standard deviation, an increase of 0.19 standard deviation is expected in mathematics work ethic, controlling other variables in the model. Mathematics work ethic had a small positive effect ($\beta = 0.19$) on science performance. This suggests that students' mathematics work ethic are likely to raise students' science performance. Less than 4% of variations in science performance were explained by mathematics work ethic respectively.

Mathematics anxiety ($\beta = -0.23$, $SE = 0.018$, $p < 0.001$) was statistically significant and negatively related to cognitive activation in mathematics. This result says that given an increase in cognitive activation of one standard deviation, a decrease of 0.23 standard deviation is expected in mathematics anxiety, controlling other variables in the model. This effect on mathematics anxiety ($\beta = -0.23$) suggests that, perceived negative medium cognitive activation in mathematics lessons is likely to lower mathematics anxiety among students. Mathematics anxiety ($\beta = -0.39$, $SE = 0.016$, $p < 0.001$) was statistically significant and negatively related to mathematics work ethic. Mathematics anxiety had a medium negative effect ($\beta = -0.39$) on mathematics work ethic. This result says that given an increase in mathematics anxiety of one standard deviation, a decrease of 0.39 standard deviation is expected in mathematics work ethic, controlling other variables in the model. This suggests that mathematics anxiety had a negative influence on students’ mathematics work ethic. About 15% of variations in mathematics work ethic were explained by mathematics anxiety. Mathematics work ethic ($\beta = 0.26$, $SE = 2.753$, $p < 0.001$) was statistically significant and positively related to mathematics performance. This result says that given an increase in mathematics work ethic of one standard deviation, an increase of 0.26 standard deviation is expected in mathematics performance, controlling other variables in the model. This suggests that mathematics work ethic had a positive influence on students' mathematics performance. About 7% of variations in mathematics performance were explained by mathematics work ethic. Mathematics work ethic ($\beta = 0.20$, $SE = 2.876$, $p < 0.001$) was statistically significant but it was positively related to science performance. This result says that given an increase in mathematics work ethic of one standard deviation, an increase of 0.20 standard deviation is expected in science performance, controlling other variables in the model. This suggests that mathematics work ethic had a positive influence on students' science performance. About 4% of variations in mathematics performance were explained by mathematics work ethic.

Research Question 1.

Does students' instrumental motivation, anxiety, and work ethic for mathematics mediate relation between cognitive-activation instruction and students' PISA test scores (plausible values) in mathematical literacy and scientific literacy?

Hypothesis testing. All paths were set to a regression weight of zero except paths between the independent variable (cognitive activation in mathematics lessons) and the dependent variables (mathematics and science performance) of the hypothesis being tested. For example, when calculating regression weights to test hypothesis 1(a), only paths in figure 3 were used. The remaining paths were fixed to zero. Additionally, direct paths between independent and dependent variables were added.

Hypothesis 1a. Cognitive-activation instructions will positively predict students' instrumental motivation to learn mathematics which will positively predict students' PISA tests scores in mathematical literacy and scientific literacy.

The meditation variable was instrumental motivation to learn mathematics. Cognitive activation in mathematics lessons was the independent variable and mathematics and science performance were the dependent variables. Testing of hypothesis 1(a) focused on the paths in figure 3. Standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.19$ and $\beta = 0.15$ respectively before a mediator variable (instrumental motivation to learn mathematics) was introduced. After instrumental motivation to learn mathematics was added in figure 3, standardized direct regression between cognitive activation and mathematics and science performance were $\beta = 0.11$ and $\beta = 0.10$ respectively.

Mediation analysis was tested using the bootstrapping method with bias-corrected confidence estimates (Preacher and Hayes, 2004). In this study, the 95% confidence interval (CI) of indirect effects was obtained with 5000 bootstrap resamples (Preacher and Hayes, 2008). Standardized indirect effect of the path (i.e. cognitive activation in mathematics lessons – instrumental motivation to learn mathematics - mathematics performance) was ($\beta = 0.07$, $SE = 0.007$, $CI = 0.054$ to 0.082). Similarly, standardized indirect effect of the path (i.e. cognitive activation in mathematics lessons – instrumental motivation to learn mathematics -science performance) was ($\beta = 0.05$, $SE = 0.007$, $CI =$ 0.034 to 0.060). Therefore, because the confidence interval does not span zero, standardized indirect effect was significant. The effects size of mediator was small, $\beta <$ 0.2. Results of the mediation analysis support the prediction that motivation to learn mathematics mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance. Consequently, part of the variance in the mathematics and science performance was explained by the indirect route through instrumental motivation to learn mathematics.

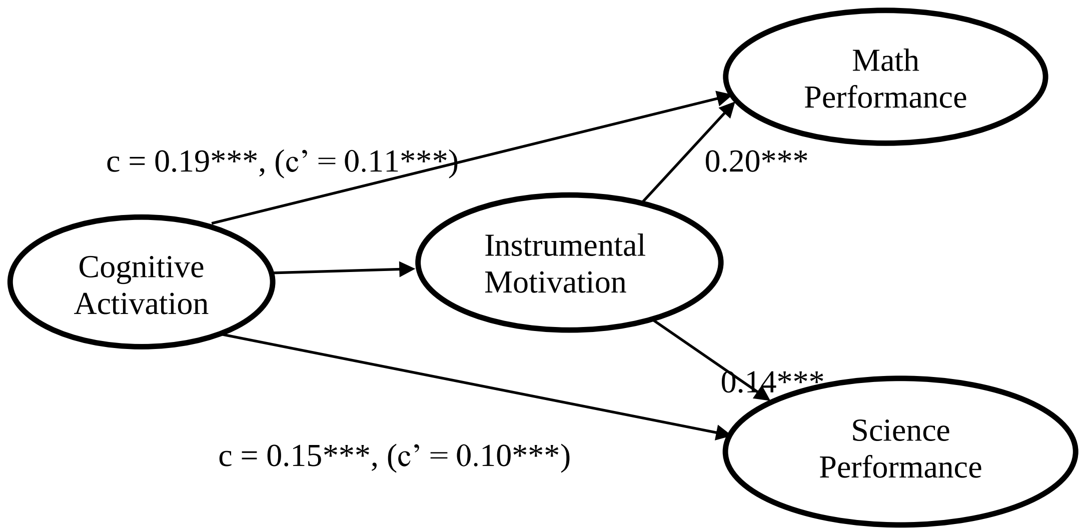


Figure 3. Standardized Parameter Estimates for Pathways between Cognitive Activation and Mathematics and Science Performance through Instrumental Motivation Variable.
$p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 15

Standardized Direct and Indirect Weights, Errors and Confidence Interval for Figure 3

Paths	Direct	Indirect	SE/Std Error	95 Cofidence Level Lower Bound	Upper Bound
Cognitive-Math	0.19***		2.597		
Cognitive-Science	0.15***		2.702		
Cognitive-Math1	0.11***		2.597		
Cognitive-Motivation	0.33***		0.021		
Cognitive-Science1	0.10***		2.875		
Motivation-Math	0.20***		2.228		
Motivation-Science	0.14***		2.347		
Cognitive-Instrumental Motivation-Math		0.07	0.007	0.054	0.082
Cognitive-Motivation-Science		0.05	0.007	0.034	0.060

Note. $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Hypothesis 1b. Cognitive-activation instruction will negatively predict students' mathematics anxiety which will negatively predict students' PISA tests scores in mathematical literacy and scientific literacy.

The meditation variable was mathematics anxiety. Cognitive activation in mathematics lessons was the independent variable and mathematics and science performance were the depended variables. Testing of hypothesis 1(b) focused on the paths in figure 4. Before the mediator variable (mathematics anxiety) was introduced standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.19$ and $\beta = 0.15$ respectively. After a mediator was added standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.08$ and $\beta = 0.05$ respectively.

Mediation analysis was tested using the bootstrapping method with bias-corrected confidence estimates (Preacher and Hayes, 2004). In this study, the 95% confidence interval (CI) of the indirect effects was obtained with 5000 bootstrap resamples (Preacher and Hayes, 2008). Standardized indirect effect of the path (i.e. cognitive activation- mathematics anxiety-mathematics performance) was ($\beta = 0.10$, $SE = 0.009$, $CI = 0.066$ to 0.118). Likewise, standardized indirect effect of the path (cognitive activation- mathematics anxiety -science performance) was ($\beta = 0.08$, $SE = 0.010$, $CI = 0.079$ to 0.101). Therefore, because the confidence interval does not span zero, standardized indirect effect was significant. The effects size of mediator was small, $\beta < 0.2$. Results of the mediation analysis support the prediction that mathematics anxiety mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance. This means part of the variance in the mathematics and science performance was explained by the indirect route through mathematics anxiety.

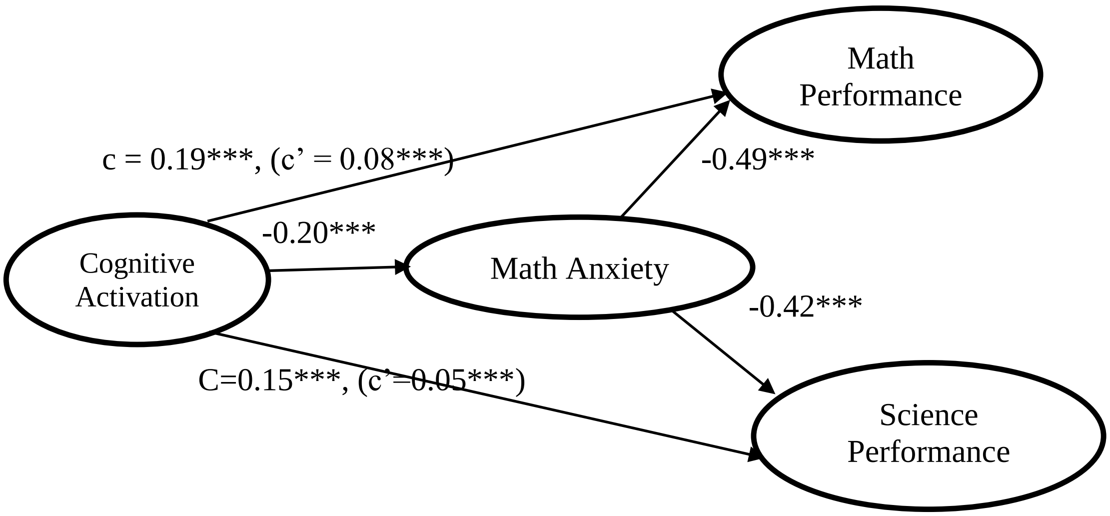


Figure 4. Standardized Parameter Estimates for Pathways between Cognitive Activation and Mathematics and Science Performance through Mathematics Anxiety Variable. *p* < 0.05, ***p* <0.01, ****p* < 0.001.

Table 16

Standardized Direct and Indirect Weights, Errors and Confidence Interval for Figure 4

Path	Direct	Indirect	SE/Std Error	95 Cofidence Level Lower Bound	Upper Bound
Cognitive-Math	0.19***		2.597		
Cognitive-Science	0.15***		2.702		
Cognitive-Math1	0.08***		2.350		
Cognitive-Science1	0.05***		2.540		
Cognitive-Anxiety	-0.20***		0.017		
Anxiety-Math	-0.49***		2.684		
Anxiety-Science	-0.42***		2.807		
Cognitive- Anxiety -Math		0.10***	0.010	0.066	0.118
Cognitive- Anxiety -Science		0.08***	0.009	0.079	0.101

*Note. p < 0.05, **p <0.01, ***p < 0.001.*

Hypothesis 1c. Cognitive-activation instruction will positively predict students' instrumental motivation for mathematics which will positively predict students' mathematics work ethic which will, in turn, predict students' PISA tests scores in mathematical literacy and scientific literacy.

The meditation variables were instrumental motivation to learn mathematics and mathematics work ethic. Cognitive activation in mathematics lessons was the independent variable and mathematics and science performance were the dependent variables. Testing of hypothesis 1(c) focused on the paths in figure 5. Before the mediator variables (instrumental motivation to learn mathematics and mathematics work ethic) were introduced standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.19$ and $\beta = 0.15$ respectively. After the first mediator (instrumental motivation to learn mathematics) was added in figure 5, standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.11$ and $\beta = 0.10$ respectively. When the second mediator was added in figure 8, standardized direct regression weights between cognitive activation and mathematics and science performance were $\beta = 0.09$ and $\beta = 0.07$ respectively.

Mediation analysis was tested using the bootstrapping method with bias-corrected confidence estimates (Preacher and Hayes, 2004). In this study, the 95% confidence interval (CI) of the indirect effects was obtained with 5000 bootstrap resamples (Preacher and Hayes, 2008). Standardized indirect effect of the path (i.e. cognitive activation- motivation to learn mathematics- mathematics work ethic - mathematics performance) was ($\beta = 0.050$, *SE* = 0.005, *CI* = 0.041 to 0.061). Similarly, standardized indirect effect of the path (cognitive activation- motivation to learn mathematics- mathematics work ethic-science performance) was (β = 0.038, *SE* = 0.005, *CI* = 0.029 to 0.047). Therefore, because the confidence interval does not span zero, standardized indirect effect was significant. The effects size of mediator was small, $\beta <$ 0.2. Results of the mediation analysis support the prediction that motivation to learn mathematics and mathematics work ethic mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance. This means part of the variance in the mathematics and science performance was explained by the indirect route through motivation to learn mathematics and mathematics work ethic.

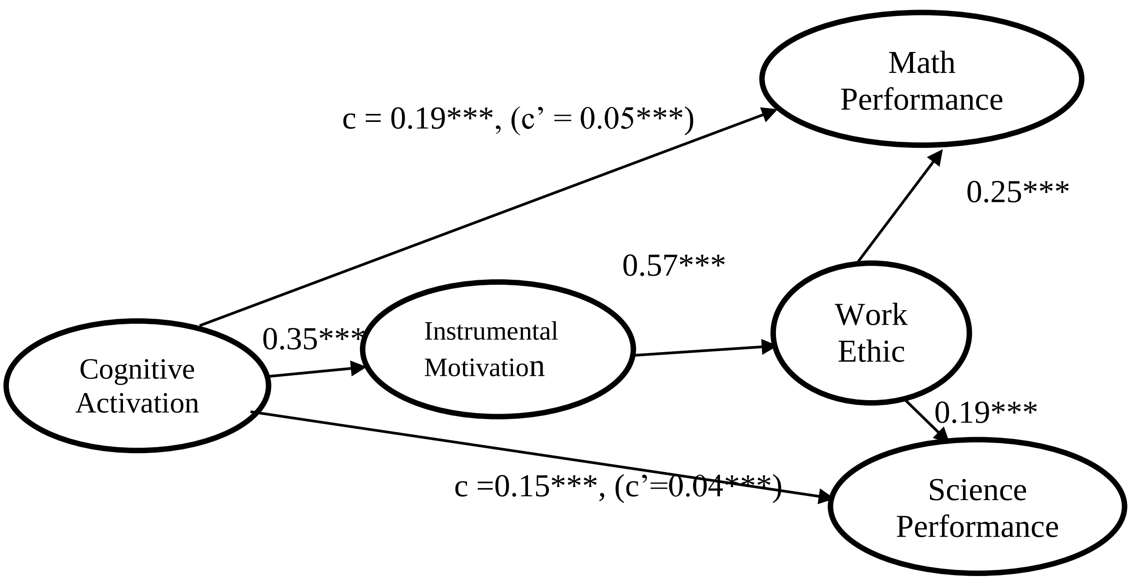


Figure 5. Standardized Parameter Estimates for Pathways between Cognitive Activation and Mathematics and Science Performance through Instrumental Motivation and Mathematics Ethic Variables. $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 17

Standardized Direct and Indirect Weights, Errors and Confidence Interval for Figure 5

Paths	Weights and Error Direct	Indirect	SE/Std Error	95 Cofidence Level Lower Bound	Upper Bound
Cognitive-Math	0.19***		2.597		
Cognitive-Science	0.15***		2.702		
Cognitive-Math1	0.11***		2.597		
Cognitive-Science1	0.10***		2.875		
Cognitive-Math2	0.09***		2.540		
Cognitive-Science2	0.07***		2.693		
Cognitive-Motivation	0.35***		0.021		
Motivation-Ethic	0.57***		0.013		
Ethic-Math	0.25***		2.792		
Ethic-Science	0.19***		2.919		
Cognitive-Motivation-Ethic-Math		0.050	0.005	0.041	0.061
Cognitive-Motivation-Ethic-Math		0.038	0.005	0.029	0.047

*Note. p < 0.05, **p <0.01, ***p < 0.001.*

Hypothesis 1d. Cognitive-activation instruction will negatively predict students' mathematics anxiety which will negatively predict students' mathematics work ethic which will, in turn, predict students' PISA tests scores in mathematics and science.

The meditation variables were mathematics anxiety and mathematics work ethic. Cognitive activation in mathematics lessons was the independent variable and mathematics and science performance were dependent variables. Testing of hypothesis 1(d) focused on the paths in figure 6. Before the mediator variables (mathematics anxiety and mathematics work ethic) were introduced, standardized direct regression weights between cognitive activation and mathematics and science performance were β = 0.19 and β = 0.15 respectively. After the first mediator (mathematics anxiety) was added in (see Figure 6), standardized direct regression weights between cognitive activation and mathematics and science performance were β = 0.08 and β = 0.05 respectively. When the second mediator was added in figure 6, standardized direct regression weights between cognitive activation and mathematics and science performance were β = 0.09 and β = 0.08 respectively.

Mediation analysis was tested using the bootstrapping method with bias-corrected confidence estimates (Preacher and Hayes, 2004). In this study, the 95% confidence interval (CI) of the indirect effects was obtained with 5000 bootstrap resamples (Preacher and Hayes, 2008). Standardized indirect effect of the path (i.e. cognitive activation-mathematics anxiety- mathematics work ethic-mathematics performance) was (β = 0.023, *SE* = 0.003, *CI* = 0.018 to 0.031). Likewise, standardized indirect effect of the path (i.e. cognitive activation- mathematics anxiety- mathematics work ethic -science performance) was (β = 0.018, *SE* = 0.013, *CI* = 0.024 to 0.024). Therefore, because the confidence interval does not span zero, standardized indirect effect was significant. The effects size of mediator was small, $\beta < 0.2$. Results of the mediation analysis support the prediction that mathematics anxiety and mathematics work ethic mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance. This means part of the variance in the mathematics and science performance was explained by the indirect route through mathematics anxiety and mathematics work ethic.

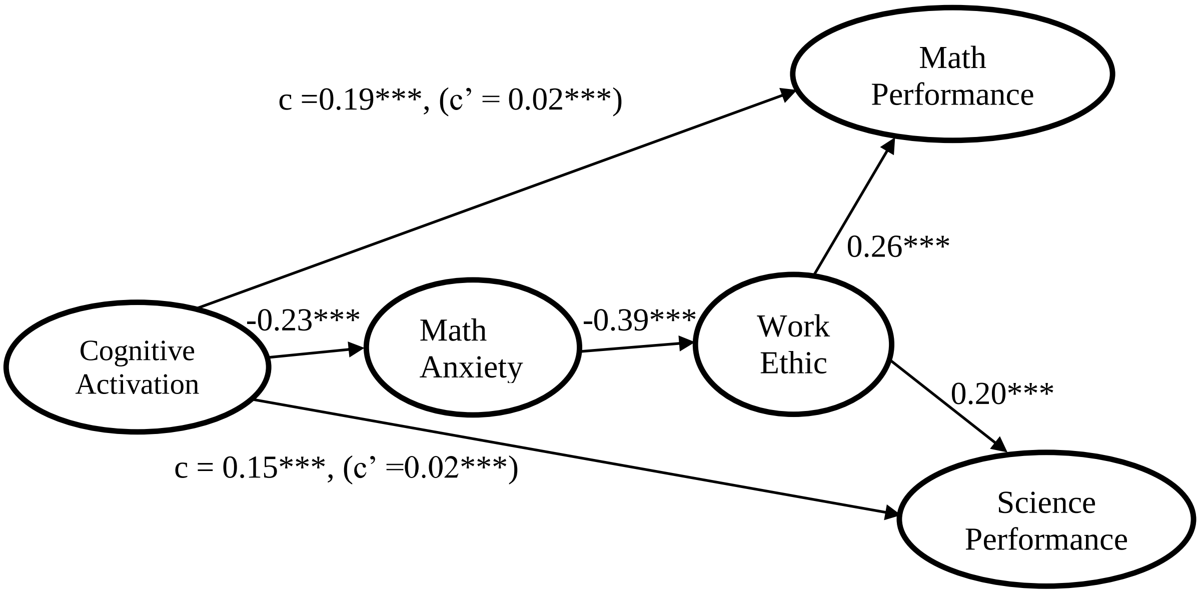


Figure 6. Standardized Parameter Estimates for Pathways between Cognitive Activation and Mathematics and Science Performance through Mathematic Anxiety and Mathematics Ethic Variables. $p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 18

Standardized Direct and Indirect Weights, Errors and Confidence Interval for Figure 6

Path	Direct	Indirect	SE/Std Error	95 Cofidence Level Lower Bound	Upper Bound
Cognitive-Math	0.19***		2.597		
Cognitive-Science	0.15***		2.702		
Cognitive-Math1	0.08***		2.350		
Cognitive-Science1	0.05***		2.540		
Cognitive-Math2	0.09***		2.490		
Cognitive-Science2	0.08***		2.641		
Cognitive-Anxiety	-0.23***		0.018		
Anxiety-Ethic	-0.39***		0.016		
Ethic- Math	0.26***		2.753		
Ethic-Science	0.20***		2.876		
Cognitive- Anxiety -Math		0.023	0.003	0.018	0.031
Cognitive- Anxiety - Science		0.018	0.003	0.013	0.024

Note. $p < 0.05$, $**p < 0.01$, $***p < 0.001$

Multi-group test. Moderation. Pairwise parameter comparisons (critical ratios for differences between parameters) was used to determine if different mediation paths were moderated by students' gender and socioeconomic status. The results of the pairwise parameter comparisons were helpful in accepting or rejecting the following the null hypothesis: (a). There is no difference among girls and boys between the independent depended variables on each path (b). There is no difference among low and high socioeconomic status students between the independent depended variables on each path. If the critical ratio (C.R) for difference among girls and boys or low and high SES students is between -1.96 to 1.96 the null hypothesis is accepted. This means there is no difference among girls and boys or among students' socioeconomic status on a given path. However, if the critical ratio for difference is a number outside the -1.96 to 1.96 ranges, then the null hypothesis is rejected.

Moderation by gender. I ran separate multi-group analyses to test the extent to which gender moderated the four mediational paths tested under research question 1. The results of the multi-group analyses for each path are presented below. The null hypothesis was rejected on the following paths based on students' gender. Moderation was tested on the following paths:

1. Cognitive activation → motivation to learn mathematics → mathematics and science performance.

Table 19 contains standardized weights (girls), standardized weights (boys), critical ratio (C.R) for girls and boys, and accept/reject null hypothesis columns. None of the relations within path 1 were moderated by gender.

Table 19

Moderation by Gender for Path 1

Paths	Standardized Weights (Girls)	Standardized Weights (Boys)	Critical Ratio (C.R) (Girls/Boys)	Accept/Reject Null Hypothesis
Cognitive → Motivation	0.30***	0.36***	1.424	Accept
Motivation → Mathematics	0.18***	0.21***	1.093	Accept
Motivation → Science	0.12***	0.15***	1.022	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

2. Cognitive activation → mathematics anxiety → mathematics and science performance.

Table 20 contains standardized weights (girls), standardized weights (boys), critical ratio (C.R) for girls and boys, and accept/reject null hypothesis columns. None of the relationships within path 2 were moderated by gender.

Table 20

Moderation by Gender for Path 2

Paths	Standardized Weights (Girls)	Standardized Weights (Boys)	Critical Ratio (C.R) (Girls/Boys)	Accept/Reject Null Hypothesis
Cognitive → Anxiety	-0.21***	-0.17***	0.884	Accept
Math → Anxiety	-0.46***	-0.50***	-0.562	Accept
Science → Anxiety	-0.39***	-0.45***	-1.661	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

3. Cognitive activation → motivation to learn mathematics → mathematics work ethic → mathematics and science performance.

Table 21 contains standardized weights (girls), standardized weights (boys), critical ratio (C.R) for girls and boys, and accept/reject null hypothesis columns. Motivation to ethic path was moderated by gender (*C.R* = 2.545), standardized regression weights were β = 0.56 (girls) and β = 0.59 (boys). This suggests that the relationship between motivation and work ethic is significant and positive for both boys and girls, but that this relationship is significantly stronger for boys than it is for girls. In other words, the positive influence of instrumental motivation on work ethic is slightly stronger for boys than it is for girls.

Table 21

Moderation by Gender for Path 3

Paths	Standardized Weights (Girls)	Standardized Weights (Boys)	Critical Ratio (C.R) (Girls/Boys)	Accept/Reject Null Hypothesis
Cognitive→ Motivation	0.31***	0.37***	1.486	Accept
Motivation→Ethic	0.56***	0.59***	2.545	Reject
Ethic→Mathematics	0.28***	0.24***	-1.753	Accept
Ethic→Science	0.22***	0.17***	-1.889	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4. Cognitive activation → mathematics anxiety → mathematics work ethic → mathematics and science performance.

Table 22 contains standardized weights (girls), standardized weights (boys), critical ratio (C.R) for girls and boys, and accept/reject null hypothesis columns. Work ethic to mathematics was moderated by gender (*C.R* = -3.336), standardized regression weights were β = 0.29 (girls) and β =0.20 (boys). This suggests that the relationship between ethic and mathematics is significant and positive for both boys and girls, but that this relationship is significantly stronger for girls than it is for boys. In other words, the positive influence of ethic on mathematics is slightly stronger for girls than it is for boys.

Similarly, work ethic to science relationship was moderated by gender (*C.R* = -2.125), standardized regression weights were β = 0.23 (girls) and β =0.18 (boys). This suggests that the relationship between work ethic and science is significant and positive for both boys and girls, but that this relationship is significantly stronger for girls than it is for boys. In other words, the positive influence of work ethic on science is slightly stronger for girls than it is for boys.

Table 22

Moderation by Gender for Path 4

Paths	Standardized Weights (Girls)	Standardized Weights (Boys)	Critical Ratio (C.R) (Girls/Boys)	Accept/Reject Null Hypothesis
Cognitive→Anxiety	-0.23***	-0.20***	0.818	Accept
Anxiety→Ethic	-0.42***	-0.39***	0.308	Accept
Ethic→Mathematics	0.29***	0.20***	-3.336	Reject
Ethic→ Science	0.23***	0.18***	-2.125	Reject

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is “accepted” otherwise “rejected”. $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Moderation by socioeconomic status. I ran separate multi-group analyses to test the extent to which socioeconomic status moderated the four mediational paths tested under research question 1. The results of the multi-group analyses for each path are presented below. Moderation was tested on the following paths:

1. Cognitive activation→ motivation to learn mathematics→ mathematics and science performance.

Table 23 contains standardized weights (low), standardized weights (high), critical ratio (C.R) for low and high socioeconomic status, and accept/reject null hypothesis columns. None of the relationships within path 1 were moderated by socioeconomic status.

Table 23

*Moderation by S*ocioeconomic Status *for Path 1*

Paths	Standardized Weights (Low)	Standardized Weights (High)	Critical Ratio (C.R) (Low/High)	Accept/Reject Null Hypothesis
Cognitive → Motivation	0.37***	0.31***	-1.518	Accept
Motivation → Math	0.22***	0.22***	0.177	Accept
Motivation → Science	0.15***	0.16***	0.089	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

2. Cognitive activation → mathematics anxiety → mathematics and science performance.

Table 24 contains standardized weights (low), standardized weights (high), critical ratio (C.R) for low and high socioeconomic status, and accept/reject null hypothesis columns. The relation between cognitive activation and mathematics anxiety was moderated by socioeconomic status (C.R = -2.469), standardized weights (Low), β = -0.14 and standardized weights (high), β = -0.22. This suggests that the relation between cognitive activation and mathematics anxiety is significant and negative for both low and high socioeconomic status students, but that this relationship is significantly stronger for low socioeconomic status students than it is for high socioeconomic status students. In other words, the negative influence of cognitive activation on mathematics anxiety is slightly stronger for low socioeconomic status students than it is for high socioeconomic status students.

Table 24

*Moderation by S*ocioeconomic Status *for Path 2*

Paths	Standardized Weights (Low)	Standardized Weights (High)	Critical Ratio (C.R) (Low/High)	Accept/Reject Null Hypothesis
Cognitive → Anxiety	-0.14***	-0.22***	-2.469	Reject
Anxiety → Math	-0.47***	-0.48***	-0.114	Accept
Anxiety → Science	-0.39***	-0.41***	-0.466	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $**p < 0.01$, $***p < 0.001$.

3. Cognitive activation → motivation to learn mathematics → mathematics work ethic → mathematics and science performance.

Table 25 contains standardized weights (low), standardized weights (high), critical ratio (C.R) for low and high socioeconomic status, and accept/reject null hypothesis columns. None of the relationships within path 3 were moderated by socioeconomic status.

Table 25

Moderation by Socioeconomic Status *for Path 3*

Paths	Standardized Weights (Low)	Standardized Weights (High)	Critical Ratio (C.R) (Low/High)	Accept/Reject Null Hypothesis
Cognitive → Motivation	0.38***	0.33***	-1.387	Accept
Motivation → Ethic	0.59***	0.55***	-1.825	Accept
Ethic → Mathematics	0.27***	0.22***	-0.836	Accept
Ethic → Science	0.20***	0.15***	-1.320	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is "accepted" otherwise "rejected". $p < 0.05$, $**p < 0.01$, $***p < 0.001$.

4. Cognitive activation → mathematics anxiety → mathematics work ethic → mathematics and science performance.

Table 26 contains standardized weights (low), standardized weights (high), critical ratio (C.R) for low and high socioeconomic status, and accept/reject null hypothesis columns. Cognitive to anxiety relation was moderated by gender (*C.R* = -2.697), standardized weights (Low), β = - 0.16 and standardized weights (high), β = -0.25. This suggests that the relationship between cognitive activation and mathematics anxiety is significant and negative for both low and high socioeconomic status students, but that this relationship is significantly stronger for low socioeconomic status students than it is for high socioeconomic status students. In other words, the negative influence of cognitive activation on mathematics anxiety is slightly stronger for low socioeconomic status students than it is for high socioeconomic status students.

Table 26

Moderation by Socioeconomic Status *for Path 4*

Paths	Standardized Weights (Low)	Standardized Weights (High)	Critical Ratio (C.R) (Low/High)	Accept/Reject Null Hypothesis
Cognitive → Anxiety	-0.16***	-0.25***	-2.697	Reject
Anxiety → Ethic	-0.33***	-0.40***	-0.950	Accept
Ethic → Mathematics	0.27***	0.23***	-0.851	Accept
Science → Ethic	0.20***	0.16***	-1.349	Accept

Note. Responses to the null hypotheses are in the 5th column. If the critical ratio (C.R) for difference is between -1.96 to 1.96 the null hypothesis is “accepted” otherwise “rejected”. $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Chapter IV Summary

Data cleaning, data analysis, and results interpretation were done in Chapter 4. Statistical package for the social sciences (SPSS) and analysis of a moment structures (AMOS) software were used in data cleaning and data analysis. Data were evenly distributed and there were no outliers. Two factors (cogntive3 and cognitive4) which did not load on their respective variables were eliminated. Although the study model did not fit the data perfectly, the model was adequate for further analysis.

Instrumental motivation to learn mathematics, mathematics anxiety and mathematics work ethic mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance. Moderation by gender and socioeconomic status was weak. Instrumental motivation to learn mathematics to mathematics work ethic and mathematics work ethic relations were moderated by gender. Cognitive activation in mathematics lessons to mathematics anxiety relation was moderated by socioeconomic status.

V: DISCUSSION

In this chapter the following subtopics were addressed, a brief review of the purpose of this study, discussion on the study results, assumptions and limitations of the study, and implications for future research. The purpose of this study was to test the indirect effects of cognitive activation in mathematics lessons (independent variable) on mathematics and science performance (dependent variables) through the following mediator variables: instrumental motivation to learn mathematics, mathematics anxiety, and mathematics work ethic. This study investigated the simultaneous effects of cognitive activation in mathematics lesson with the mediator variables on students' mathematics and science performance. Additionally, moderation effects were investigated based on students' gender and socioeconomic status. Structural equation modeling (SEM) technique and analysis of a moment structures (AMOS) facilitated the development of an integrated model which included all variables.

This study also utilized the control-value theory of achievement emotions framework. The control-value theory posited that environmental characteristics such as quality of instructions influence cognitive appraisals among students and academic outcomes (Pekrun, 2006). Cognitive appraisals of students' capabilities to control learning activities and outcomes (e.g., perceived competence) and their valuing of academic tasks have been found to influence their achievement emotions such as anxiety and pride as well as academic outcomes.

Reviewed studies (Baumert et al., 2010; M. L. Chang, 2009; Cheon et al., 2016; Woodward & Ono, 2004) have shown that cognitive activation in mathematics ignites curiosity among students and help teachers to identify and assist struggling students. Use of cognitive strategies in mathematics lessons enable teachers to challenge students regularly by asking follow-up questions or allowing students to try alternative ways to solve a problem. According to several studies (Ashcraft, 2002; Baumert et al., 2010; Braver et al., 2014; Förtsch, Werner, Dorfner, von Kotzebue, & Neuhaus, 2016), cognitive activation in mathematics lessons and students' instrumental motivation to learn mathematics were positively related to improved mathematics and science performance. However, mathematics anxiety among students negatively impacted students' mathematics and science performance.

Although different studies (Areepattamannil et al., 2016; Ashcraft, 2002; Morgan, Hodge, Wells, & Watkins, 2015; Tella, 2007) have established the influence of cognitive activation in mathematics lessons, instrumental motivation to learn mathematics, mathematics anxiety and students' mathematics work ethic influence students' mathematics and science performance, this study focused on how the interrelationships among these four factors may influence students' mathematics and science performance. Finally, moderation on each mediated path was examined based on students' gender and socioeconomic status.

Discussion of Results

A SEM model was constructed using the study variables. Results of this study found support for the study's hypotheses that cognitive activation in mathematics lessons positively predicted students' instrumental motivation to learn mathematics which positively predicted students' mathematics and science performance. Similarly, cognitive activation in mathematics lessons negatively predicted students' mathematics anxiety and negatively predicted students' mathematics and science performance.

Mathematics anxiety, instrumental motivation to learn mathematics and students' mathematics work ethic mediated the relation between cognitive activation in mathematics lessons and mathematics and science performance.

Additionally, these results were supported by the control-value theory of achievement emotions (CVTAE). The control-value theory of achievement emotions posits that when students understand course content, they tend to have a positive attitude towards a subject (Areepattamannil et al., 2016; Pekrun, 2006). Positive attitudes towards a subject are manifested by students' dedication, for example, students are self-driven to seek help and their ability to "bounce back" after setback, for instance, failure in a test. Several studies (Bishop Smith et al., 2012; Förtsch, Werner, Dorfner, et al., 2016; Linder et al., 2015; Pitsia et al., 2016) investigated the relations among this study's latent variables and obtained similar results.

Perceived use of cognitive activation strategies in mathematics lessons was a good bargain "two for a price of one." Cognitive activation strategies in mathematics lessons had the potential to instrumentally motivate students as well as decrease mathematics anxiety among students (OECD, 2014). Similar results were also found in this study (Baumert et al., 2010; Bishop Smith et al., 2012; Cantley et al., 2017; Maloney et al., 2014). Skillful implementation of cognitive strategies in mathematics lessons encourages students' engagements and valuing of the subject (Baumert et al., 2010; Bishop Smith et al., 2012; Förtsch, Werner, Dorfner, et al., 2016). For example, when a teacher presents problems in different contexts to check if students have understood the concepts or a teacher who helps students to learn from their mistakes. The use of these strategies may inspire self-belief in students' ability (Cheon et al., 2016; Pekrun, 2006).

According to Pekrun, the control-value theory of achievement emotions, self-belief in students' ability tend to motivate them. Motivation is positively and significantly related to improved mathematics and science performance (Ashcraft, 2002; Braver et al., 2014; Förtsch, Werner, Dorfner, et al., 2016). Results of this study were aligned with Pekrun's theory. For example, cognitive activation in mathematics lessons and instrumental motivation to learn mathematics were positively and statistically significantly related to mathematics and science performance.

The control-value theory of achievement emotions (CVTAE) also suggested that anxiety triggers fear of failure or self-doubt in a student's ability to deal with academic challenges (solving mathematics problems) which increases the likelihood of poor performance. In this study, mathematics anxiety was negatively and statistically significantly related to students' mathematics work ethic and their mathematics and science performance. The effect sizes of both relations were medium.

Previous studies have investigated the effects of some of the variables (mathematics anxiety, instrumental motivation, mathematics and science performance) used in this study in a piecemeal fashion (Artemenko et al., 2015; Halpern et al., 2007; Maloney et al., 2014). However, in this study all variables were examined in a unified, as opposed to piecemeal fashion which is more "realistic" to students learning experience compared to piecemeal investigating each independent and dependent variable in isolation.

This study found that instrumental motivation to learn mathematics mediated the path between cognitive activation in mathematics and mathematics and science performance. Likewise, mathematics anxiety mediated the path between cognitive activation in mathematics and mathematics and science performance. Additionally, instrumental motivation to learn mathematics and mathematics work ethic mediated relations between cognitive activation in mathematics lessons and students' in mathematics and science performance. Finally, mathematics anxiety and mathematics work ethic mediated relations between cognitive activation in mathematics lessons and students' in mathematics and science performance. The mediation effects were statistically significant, but typically had medium effect sizes. Preceding studies did not investigate mediational roles of mediator variables used in this study (Areepattamannil, 2014; Areepattamannil et al., 2016; Novak & Tassell, 2017). However, studies on instrumental motivation to learn mathematics (independent variable) and mathematics and science performance (dependent variable) found a positive and significant relationship between these variables (Dailey, 2009; Middleton & Spanias, 1999; Pitsia et al., 2016; Tella, 2007). Similar conclusion was arrived at in this study.

This study made several contributions to the current literature. First, using analytical capabilities of statistical package for the social sciences (SPSS), analysis of a moment structures (AMOS) and structural equation model (SEM) this study investigated relations, mediation and moderation of several variables simultaneously. Previously, high cost of data and slow computing capabilities stalled the utilization of these analytical approaches. Second, inclusion of parallel and serial mediated in the SEM model provided in-depth insights on the relations among variables. Third, this study incorporated mathematics work ethic variable. This variable is relatively new. Data were collected using this instrument in the year 2012 for the first time. In this study mathematics work ethic was used in a serial mediation with instrumental motivation and mathematics anxiety forming two separate paths (i.e. cognitive activation in mathematics lessons to instrumental motivation to learn mathematics to mathematics work ethics to mathematics and science performance and cognitive activation in mathematics lessons to mathematics anxiety to mathematics work ethics to mathematics and science performance). Each path was mediated.

There was limited support for the hypothesis on the moderation effects of students' gender and socioeconomic status. Students' gender and socioeconomic status moderated less than 14% of the mediated paths. According to Schulz (2005), the effects of students' socioeconomic status on academic performance are easier to detect when the constructs are investigated at school level as opposed to students level. While acknowledging that there are gender differences among students in Australia, these differences are less pronounced in Australia and other Organization for Economic Cooperation and Development (OECD) member countries compared to less developed countries or countries which embrace gender-biased practices (OECD, 2014). Similarly differences among Australian students based on their socioeconomic status relatively narrower (OECD, 2014). Additionally, many OECD member countries have developed specific programs which uplift disadvantaged groups of people in their societies. Therefore, the lack of moderation effects by gender and socioeconomic status could be a result of these programs being effective.

Assumptions and Limitations

Primarily, PISA assessments are meant for comparison of education systems among participating countries as opposed to specific educational needs of a particular country (OECD, 2014). Therefore, the findings of this study may not form the basis of initiating wide-reaching education reforms in participating countries (Australia), although this study's findings offer valuable lessons on the state of the Australian education system. Education reforms should be informed by assessments which are closely linked to the curriculum in each country or state (OECD).

PISA assessments rely on rotated student context questionnaires to assess non-cognitive outcomes, rotation cognitive skills test and data imputation to cover wide content and population at a relatively low cost, and there are discrepancies between imputed and actual data (Wu, 2002). According to Wu, plausible values should not substitute the actual results. Therefore, precaution should be taken when making critical decisions based on the findings of this study.

The use of pre-existing data poses several challenges. First, pre-existing data is rigid, for example, changes cannot be done on data collection instruments to cater for minor changes in the study design. For instance, I would have liked to change the instrumental motivation to learn mathematics to motivation to learn mathematics. Instrumental motivation to learning mathematics is a subset of motivation construct which many students may not be familiar with. Likewise, focusing on a subset of motivation as opposed to motivation in general limits the generalization of the study findings. Second, converting pre-existing data from the original storage format to a format suitable for analysis is time-consuming and susceptible to errors.

Implications for Practice

Results of this have affirmed several teaching and learning practices embraced by educators and students alike. For example, this study found that cognitive activation in mathematics lessons reduced mathematics anxiety and improved instrumental motivation to learn mathematics among students. This may suggest that, allowing students to attempt different approaches in solving mathematics problems and helping them whenever they need help can positively influence students in mathematics and science. Second, part of the statements in the cognitive activation instrument focused on mathematics content delivery (teaching strategies). While teachers' mastery of the subjects (mathematics and science) content is a commendable achievement and a huge advantage to his or her students' results, this study seem to suggest that mathematics content delivery plays a crucial role in improving mathematics and science performance. Third, results show that both instrumentally motivated and mathematics anxious may influence students' mathematics work ethic. The negative impact of mathematics anxiety was mediated by mathematics work ethic to a small but significant positive effect on mathematics and science performance. For teachers interested in fostering their students' work ethic, these results suggest that addressing students' mathematics anxiety and instrumental motivation may help them adopt a stronger mathematics work ethic.

Implications for Future Research

Future studies should consider using data with minimal or no imputed data. PISA assessments are designed to assess students from different countries to facilitate comparisons among different education systems. Logistical challenges do not allow PISA to collect "complete" data from each student. However, to improve on the study findings it is necessary to use data obtained from each student instead of imputing students' responses. For example, with a smaller sample size it will be easy and cheaper to administer the assessment to each student, therefore, obtaining a better quality of data. Second, instead of using PISA data future studies could use domestically (Australia) sourced data. The findings of a study based on domestically sourced data will be a relatively better option for decision makers by different stakeholder as opposed to study findings based on PISA data.

PISA assignments are administered three to six months before the completion of compulsory education by participants. In many countries and specifically in Australia students are simultaneously preparing for their final examination in high school. This period is marked by high levels of anxiety and time constraints for any activities unrelated to their examination preparations. Likewise, survey students on mathematics anxiety in the last three months of their high school can yield misleading responses because mathematics anxiety and test anxieties tend to relate to each other and it may be challenging for students to distinguish the effect of either of them.

Previous studies (Schulz, 2005; Shafiq, 2013) mentioned that, assessing the effects of students' socioeconomic status on their performance in examinations are more pronounced at the school level as opposed to examining the effects of students' socioeconomic status on their performance in examinations at individual level which was the focus of this study. Future studies should use hierarchical design to study the socioeconomic status construct. Future studies should run the mediation section of this study with a learning software which is flexible than AMOS. For example, when testing for serial and/or parallel mediation in AMOS, AMOS calculates the mediation effects of all paths not the results of each path. Therefore, it is challenging to interpret the results accurately.

Finally, working “backwards” may yield useful insights information. For example, cluster the dependent variables based on students’ performance (i.e., low, medium and high), then investigate relation among independent variables of each cluster. Results of this study will help researchers to diagnose or formulated general descriptions of students in each cluster. For instance, researchers may conclude that students in low cluster tend to experience mathematics anxiety and poor work ethic. This information would be valuable to different people in education sectors, such as parents, education advisors and instructors among others.

Summary and Conclusion

This study investigated the relations of motivational and affective factors which influence students' mathematics and science performance. The study incorporated motivational and affective factors which have been researched on extensively, in the past like mathematics anxiety and motivation (instrumental) to learn mathematics. Likewise, relatively new affective factor like mathematics work ethic was integrated into the study. The guided by the control-value theory of achievement emotions and utilizing structural equation model (AMOS) this study was able to investigate influence the motivational and affective factors simultaneously.

The results of this study supported previous studies findings, for example, the negative effects of mathematics anxiety to students' performance in mathematics and science were affirmed. Also the positive relationship between cognitive activation and instrumental motivation to learn mathematics were confirmed. The positive effect on students' mathematics and science performance by instrumental motivation to learn mathematics were also supported by previous studies (Lazarides et al., 2017; Pitsia et al., 2017; Sastre-Vazquez et al., 2013).

Likewise, this study's results were aligned with the assumptions of the control-value theory of achievement emotions. The control-value theory of achievement emotions posits that students' understanding of the subject content, is likely to instill a sense of control (ownership or "feeling in-charge") and probably make students value learning. The use of cognitive activation strategies in mathematics lessons is intended to "empower" students, reduce mathematics anxiety and instrumental motivate them to improve their mathematics and science performance.

Finally, although this study has contributed to the current literature in the study of motivational and affective factors there is plenty of room to explore new relations by using new methodologies. Similarly, there are opportunities to improve and challenge this study's results, which I have suggested in the implications for future research section.

APPENDIX SECTION

The data instruments and sample questions were obtained from PISA 2012 (Park & Hill, 2016).

Cognitive activation in mathematics lessons

Item parameters for cognitive activation in mathematics lessons

Thinking about the mathematics teacher that taught your last mathematics class How often does each of the following happen?					
		Always or almost always	Often	Sometimes	Never or rarely
a	The teacher asks questions that make us reflect on the problem				
b	The teacher gives problems that require us to think for an extended time				
c	The teacher asks us to decide on our own procedures for solving complex problems				
d	The teacher presents problems for which there is no immediately obvious method of solution				
e	The teacher presents problems in different contexts so that students know whether they have understood the concepts				
f	The teacher helps us to learn from mistakes we have made				
g	The teacher asks us to explain how we have solved a problem				
h	The teacher presents problems that require students to apply what they have learned to new contexts				
i	The teacher gives problems that can be solved in several different ways				

Instrumental motivation for mathematics

Item parameters for instrumental motivation for mathematics

Thinking about your views on mathematics: to what extent do you agree with the following statements?					
		Strongly Agree	Agree	Disagree	Strongly disagree
a	Making an effort in mathematics is worth it because it will help me in the work that I want to do later on				
b	Learning mathematics is worthwhile for me because it will improve my career prospects or chances				
c	Mathematics is an important subject for me because I need it for what I want to study later on				
d	I will learn many things in mathematics that will help me get a job				

Mathematics Anxiety

Item parameters for mathematics anxiety

Thinking about studying mathematics: to what extent do you agree with the following statements?					
		Strongly agree	Agree	Disagree	Strongly disagree
a	I often worry that it will be difficult for me in mathematics classes				
b	I get very tense when I have to do mathematics homework				
c	I get very nervous doing mathematics problems				
d	I feel helpless when doing a mathematics problem				
e	I worry that I will get poor grades in mathematics				

Mathematics work ethic

Item parameters for mathematics work ethic

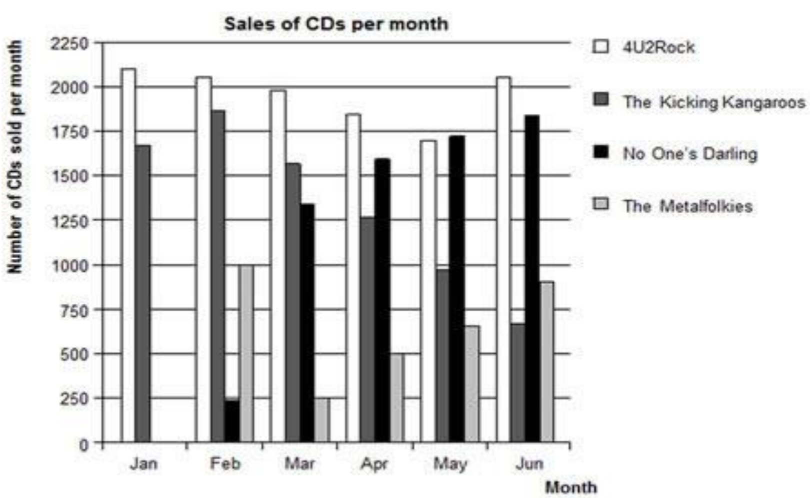
Thinking about the mathematics you do for school: to what extent do you agree with the following statements?					
		Strongly Agree	Agree	Disagree	Strongly Disagree
a	I finish my homework in time for mathematics class				
b	I work hard on my mathematics homework				
c	I am prepared for my mathematics exams				
d	I study hard for mathematics quizzes				
e	I keep studying until I understand mathematics material				
f	I pay attention in mathematics class				
g	I listen in mathematics class				
h	I avoid distractions when I am studying mathematics				
i	I keep my mathematics work well organized				

APPENDIX B: PISA 2012 MATHEMATICS (SAMPLE QUESTIONS)
LEVEL 1

At Level 1, students can explore a problem scenario only in a limited way, but tend to do so only when they have encountered very similar situations before. Based on their observations of familiar scenarios, these students are able only to partially describe the behavior of a simple, everyday device. In general, students at Level 1 can solve straightforward problems provided there is only a simple condition to be satisfied and there are only one or two steps to be performed to reach the goal. Level 1 students tend not to be able to plan ahead or set sub-goals.

TEST QUESTIONS (LEVEL 1): CHARTS

In January, the new CDs of the bands 4U2Rock and The Kicking Kangaroos were released. In February, the CDs of the bands No One's Darling and The Metalfolkies followed. The following graph shows the sales of the bands' CDs from January to June.



QUESTION

In which month did the band No One's Darling sell more CDs than the band The Kicking Kangaroos for the first time?

A No Month B March C **April** D May

LEVEL 2

At Level 2, students can explore an unfamiliar problem scenario and understand a small part of it. They try, but only partially succeed, to understand and control digital devices with unfamiliar controls, such as home appliances and vending machines. Level 2 problem-solvers can test a simple hypothesis that is given to them and can solve a problem that has a single, specific constraint. They can plan and carry out one step at a time to achieve a sub-goal, and have some capacity to monitor overall progress towards a solution.

TEST QUESTIONS (LEVEL 2): HELEN THE CYCLIST

Helen has just got a new bike. It has a speedometer, which sits on the handlebar.

The speedometer can tell Helen the distance she travels and her average speed for a trip.

QUESTION

On one trip, Helen rode 4 km in the first 10 minutes and then 2 km in the next 5 minutes. Which one of the following statements is correct?

A Helen's average speed was greater in the first 10 minutes than in the next 5 minutes.

B **Helen's average speed was the same in the first 10 minutes and in the next 5 minutes.**

C Helen's average speed was less in the first 10 minutes than in the next 5 minutes.

D It is not possible to tell anything about Helen's average speed from the information given.

LEVEL 3

At Level 3, students can handle information presented in several different formats. They can explore a problem scenario and infer simple relationships among its components. They can control simple digital devices, but have trouble with more complex devices. Problem-solvers at Level 3 can fully deal with one condition, for example, by generating several solutions and checking to see whether these satisfy the condition. When there are multiple conditions or inter-related features, they can hold one variable constant to see the effect of change on the other variables. They can devise and execute tests to confirm or refute a given hypothesis. They understand the need to plan ahead and monitor progress, and are able to try a different option if necessary.

TEST QUESTIONS (LEVEL 3): WHICH CAR?

Chris has just received her car driving license and wants to buy her first car.

This table below shows the details of four cars she finds at a local car dealer.

Model:	Alpha	Bolte	Castel	Dezal
Year	2003	2000	2001	1999
Advertised price (zeds)	4800	4450	4250	3990
Distance travelled (kilometres)	105 000	115 000	128 000	109 000
Engine capacity (litres)	1.79	1.796	1.82	1.783

QUESTION

Which car's engine capacity is the smallest?

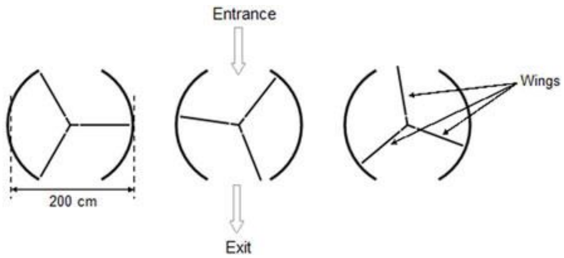
A Alpha B Bolte C Castel D **Dezal**

LEVEL 4

At Level 4, students can explore a moderately complex problem scenario in a focused way. They grasp the links among the components of the scenario that are required to solve the problem. They can control moderately complex digital devices, such as unfamiliar vending machines or home appliances, but they don't always do so efficiently. These students can plan a few steps ahead and monitor the progress of their plans. They are usually able to adjust these plans or reformulate a goal in light of feedback. They can systematically try out different possibilities and check whether multiple conditions have been satisfied. They can form a hypothesis about why a system is malfunctioning, and describe how to test it.

TEST QUESTIONS (LEVEL 4): REVOLVING DOOR

A revolving door includes three wings that rotate within a circular-shaped space. The inside diameter of this space is 2 metres (200 centimetres). The three door wings divide the space into three equal sectors. The plan below shows the door wings in three different positions viewed from the top.



QUESTION

The door makes 4 complete rotations in a minute. There is room for a maximum of two people in each of the three door sectors.

What is the maximum number of people that can enter the building through the door in 30 minutes?

A 60 B 180 C 240 D **720**

LEVEL 5

At Level 5, students can systematically explore a complex problem scenario to gain an understanding of how relevant information is structured. When faced with unfamiliar, moderately complex devices, such as vending machines or home appliances, they respond quickly to feedback in order to control the device. In order to reach a solution, Level 5 problem-solvers think ahead to find the best strategy that addresses all the given constraints. They can immediately adjust their plans or backtrack when they detect unexpected difficulties or when they make mistakes that take them off course.

TEST QUESTIONS (LEVEL 5): CLIMBING MOUNT FUJI

Mount Fuji is a famous dormant volcano in Japan.

QUESTION

The Gotemba walking trail up Mount Fuji is about 9 kilometers (km) long. Walkers need to return from the 18 km walk by 8 pm. Toshi estimates that he can walk up the mountain at 1.5 kilometers per hour on average, and down at twice that speed. These speeds take into account meal breaks and rest times. Using Toshi's estimated speeds, what is the latest time he can begin his walk so that he can return by 8 pm?

Type your answer below and hit Submit button

THE CORRECT ANSWER IS - 11 AM

LEVEL 6

At Level 6, students can develop complete, coherent mental models of diverse problem scenarios, enabling them to solve complex problems efficiently. They can explore a scenario in a highly strategic manner to understand all information pertaining to the problem. The information may be presented in different formats, requiring interpretation and integration of related parts. When confronted with very complex devices, such as home appliances that work in an unusual or unexpected manner, they quickly learn how to control the devices to achieve a goal in an optimal way. Level 6 problem-solvers can set up general hypotheses about a system and thoroughly test them. They can follow a premise through to a logical conclusion or recognize when there is not enough information available to reach one. In order to reach a solution, these highly proficient problem-solvers can create complex, flexible, multi-step plans that they continually monitor during execution. Where necessary, they modify their strategies, taking all constraints into account, both explicit and implicit.

TEST QUESTIONS (LEVEL 6): HELEN THE CYCLIST

Helen has just got a new bike. It has a speedometer that sits on the handlebar. The speedometer can tell Helen the distance she travels and her average speed for a trip.

QUESTION

Helen rode her bike from home to the river, which is 4 km away. It took her 9 minutes. She rode home using a shorter route of 3 km. This only took her 6 minutes. What was Helen's average speed, in km/h, for the trip to the river and back?

Type your answer below and hit Submit button

Average speed for the trip: .... km/h

THE CORRECT ANSWER IS – 28

APPENDIX C: DATA ANALYSIS SCREENSHOTS

C.1.Pattern Matrix[a]

	Component			
	1	2	3	4
Eth2R	.837			
Eth4R	.800			
Eth6R	.785			
Eth1R	.777			
Eth8R	.771			
Eth7R	.758			
Eth9R	.753			
Eth5R	.729			
Eth3R	.682			
Cog5R		.747		
Cog8R		.745		
Cog2R		.732		
Cog1R		.729		
Cog9R		.716		
Cog7R		.697		
Cog6R		.681		
Cog3R		.656		
Cog4R		.639		
Anx3R			.847	
Anx1R			.818	
Anx2R			.789	
Anx5R			.774	
Anx4R			.722	
Mot3R				.912
Mot4R				.888
Mot2R				.883
Mot1R				.857

Extraction Method: Principal Component Analysis.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

C.2. Communalities

	Initial	Extraction
Mot1R	1.000	.776
Mot2R	1.000	.795
Mot3R	1.000	.782
Mot4R	1.000	.778
Anx1R	1.000	.645
Anx2R	1.000	.670
Anx3R	1.000	.690
Anx4R	1.000	.593
Anx5R	1.000	.556
Eth1R	1.000	.580
Eth2R	1.000	.669
Eth3R	1.000	.597
Eth4R	1.000	.607
Eth5R	1.000	.610
Eth6R	1.000	.612
Eth7R	1.000	.601
Eth8R	1.000	.549
Eth9R	1.000	.537
Cog1R	1.000	.554
Cog2R	1.000	.518
Cog3R	1.000	.417
Cog4R	1.000	.374
Cog5R	1.000	.561
Cog6R	1.000	.518
Cog7R	1.000	.490
Cog8R	1.000	.572
Cog9R	1.000	.505

Extraction Method: Principal Component Analysis.

C.3.Pattern Matrix[a]

	Component			
	1	2	3	4
Eth2R	.837			
Eth4R	.801			
Eth6R	.782			
Eth1R	.777			
Eth8R	.771			
Eth7R	.755			
Eth9R	.753			
Eth5R	.729			
Eth3R	.682			
Cog8R		.778		
Cog5R		.766		
Cog1R		.748		
Cog7R		.736		
Cog6R		.733		
Cog9R		.722		
Cog2R		.711		
Anx3R			.846	
Anx1R			.818	
Anx2R			.788	
Anx5R			.773	
Anx4R			.721	
Mot3R				.912
Mot4R				.887
Mot2R				.880
Mot1R				.856

Extraction Method: Principal Component Analysis.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

C.4.Communalities

	Initial	Extraction
Mot1R	1.000	.776
Mot2R	1.000	.795
Mot3R	1.000	.783
Mot4R	1.000	.778
Anx1R	1.000	.645
Anx2R	1.000	.669
Anx3R	1.000	.690
Anx4R	1.000	.593
Anx5R	1.000	.557
Eth1R	1.000	.580
Eth2R	1.000	.669
Eth3R	1.000	.597
Eth4R	1.000	.608
Eth5R	1.000	.611
Eth6R	1.000	.612
Eth7R	1.000	.602
Eth8R	1.000	.549
Eth9R	1.000	.537
Cog1R	1.000	.573
Cog2R	1.000	.488
Cog5R	1.000	.579
Cog6R	1.000	.573
Cog7R	1.000	.533
Cog8R	1.000	.609
Cog9R	1.000	.508

Extraction Method: Principal Component Analysis.

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