A Cross-national Study of Mathematics Achievement Via Three-level Multilevel Models

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ABSTRACT

The present study explored the effects of the national and cultural contexts on students' mathematics achievement. The study also investigated the nature and magnitude of student-level (level 1), school-level (level 2), and country-level (level 3) factors that are associated with math achievement. The Program for International Student Assessment (PISA) 2018 datasets were used. The main predictors focusing on this study included university admission procedure and the country's culture of mindsets about intelligence at level 3, indicating extra-curricular activities at level 2, growth mindset, and resilience self-efficacy at level 1. Other than main predictors, various predictors including country's characteristics, school characteristics, school climate factors, students' demographic characteristics, and non-cognitive abilities were added in the analysis to examine the main predictors are statistically significant after controlling for other predictors. The findings of HLM analysis showed that mathematics achievement is associated with national and cultural contexts since the study found 31.30% of the total variation was accounted for level 3 in math achievement. Also, the significant findings of the study indicated that university admission procedure was significantly associated with country-mean math achievement while the country's culture of mindsets about intelligence was not at level 3. At level 2, providing extra-curricular activities in school was a significant predictor for math achievement. At level 1, a growth mindset and information and Communication Technology (ICT) usage were positively associated with math achievement. The other significant predictors for math achievement were found in the model. In addition, the study found that the compositional effect of ICT usage explained a significant amount of between schools and countries variance even after controlling for other predictors in the analysis. Moreover, the study

found several counterintuitive association phenomena due to shift of meaning. These findings were explained in terms of practical and theoretical implications for policymakers, educators, and researchers to improve students' mathematics achievement.

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GENERAL AUDIENCE ABSTRACT

Policymakers and researchers have been concerned about the shortage of students pursuing STEM disciplines in the United States despite the increasing demand for STEM professionals. Since mathematical skills play an important role in a nation's economic development, improving mathematics performance is essential for developing professional STEM workers. Therefore, conducting a cross-national comparative study of mathematics achievement is needed to provide a useful empirical perspective and deeper understanding of mathematics performance. The present study examined the association of diverse predictors at the country-, school-, and student-level with math achievement using multilevel modeling which is also called hierarchical linear modeling (HLM). It was found that university admission procedure was significantly associated with country-mean math achievement at the country-level. Also, providing extra-curricular activities in school was a significant predictor for math achievement at the school-level and a growth mindset and information and Communication Technology (ICT) usage were positively associated with math achievement at the student-level. In addition, the study found the positive compositional effect of ICT usage at school- and country-level which indicates that developing the infrastructure of ICT in school and country should be needed to for high and sustainable students' math achievement. Moreover, the study found several counterintuitive association phenomena due to shift of meaning. These findings were explained in terms of practical and theoretical implications for policymakers, educators, and researchers to improve students' mathematics achievement.

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Chapter 1 Introduction

Background of the Study

Understanding mathematics achievement has been a major research concern because mathematical skills play an important role not only in a nation's economic development (Hanushek & Woessmann, 2008) but in scientific and technological development (Enu & Nkum, 2015). Furthermore, mathematics skills are fundamental to understanding other disciplines such as engineering, science, social sciences, and the arts (Patena & Dinglasan, 2013). It is also crucial for individuals' educational and financial success, academic motivation, attained socioeconomic status (SES), and career development (Ritchie & Bates, 2013; Siegler et al., 2012). A strong mathematics foundation is needed to succeed in STEM (science, technology, engineering, and mathematics) fields and plays an important role in integrated STEM education (Maass et al., 2019).

Since it has been widely accepted that mathematics underpins STEM disciplines, improving mathematics performance is essential for developing professional STEM workers. Developing STEM professionals is important to maintain global competitiveness and promote technological innovation. However, policymakers and researchers have been concerned about the shortage of students pursuing STEM disciplines in the United States despite the increasing demand for STEM professionals. According to a survey from the Pew Research Center (Kennedy et al., 2020), more than 50 percent of U.S students answered they don't want to pursue STEM degrees since they think it's too demanding for them. However, the U.S would need to increase its professionals in STEM fields for the nation's growth. A report from the President's Council of Advisors on Science and Technology (Olson & Riordan, 2012) showed that approximately more than one million more STEM professionals at the current rate will be needed to maintain a nation's historical preeminent position in science and technology.

Due to the lack of STEM professionals, the U.S is highly dependent on foreign workers in STEM fields (Neuhauser & Cook, 2016). According to the report from the National Center for Science and Engineering Statistics (NCSES), the enrollment of foreign graduate students in Science and Engineering increases, while the enrollment of domestic graduate students in those fields decreases (Heuer et al., 2014). Han and Appelbaum (2016) argued that U.S firms and policymakers should give opportunities to international STEM students to remain in the country for future science and technology innovation. Accordingly, the proportion of foreign-born STEM workers is increasing. The report that used the data from the American Community Survey (ACS) said that the foreign-born STEM workforce comprised one quarter in 2015, which had more than doubled from that of 1990, and the proportion will continue to increase (Anderson, 2016).

One of the causes of a shortage of STEM professionals in the U.S is the low mathematics achievement of adolescents. Students in the U.S are lagging behind the world in mathematics performance. According to the 2018 Program for International Student Assessment (PISA), the U.S. ranked 36th out of 79 countries and regions that participated in the mathematics performance test and ranked 31st among 35 industrialized countries that are members of the Organization for Economic Cooperation and Development (OECD) which is near the bottom (Thomson et al., 2019). Moreover, there was a continual decline in average mathematics achievement scores on the Trend in International Mathematics and Science Study (TIMSS) from 2011 to 2019 among fourth-grade students and from 2015 to 2019 among eighth-grade students in the U.S. (Mullis et al., 2020). Especially, students from Asian countries such as Singapore, South Korea, and Japan further outstripped U.S students. According to the TIMSS 2019 International Results in Mathematics, the average eighth-grade mathematics score in the United States from TIMSS 2019 was 515 while scores in other leading countries such as South Korea, Singapore, and Japan were about 100 points higher.

Moreover, U.S students have experienced the challenge of educational equity in mathematics. The results of the meta-analysis that was conducted by using data from the National Assessment of Educational Progress (NAEP) from 1990 to 2011 showed that there were stable gender gaps in mathematics and science achievement for students in the U.S (Reilly et al., 2015). Also, there are ongoing racial/ethnic and socioeconomic gaps in mathematics performance, which those African American students who are in lower socioeconomic groups are the most vulnerable to mathematics achievement (William, 2012). Furthermore, there is a persistent disparity in academic achievement across states. According to the NAEP, underperforming states were mostly located in the south or the southwest areas. Hansen et al. (2018) stated that "Unless we rapidly increase the rates at which we close our race-, ethnicity-, and income-based gaps, unequal access to education and the consequences of this inequality will affect students today as well as subsequent generations" (para. 15).

Adolescence is a critical period of cognitive development and learning competencies such as critical thinking and problem-solving (Steinberg, 2005), and adolescents can apply those abilities later in their life. The middle school and high school years are critical years for students in achieving mathematics. Since mathematics is a sequential subject, building math performance in middle school and high school is critical for later advanced courses in higher education and beyond. Especially, tenth grade is an important year because students generally start to learn Algebra in tenth grade (US Department of Education, 2018). Educators believe that Algebra is the foundation of logic and critical thinking, and students need to complete Algebra to improve advanced mathematics skills and achieve higher educational opportunities (Chazan, 2000). Therefore, exploring the most to the least important factors associated with secondary students' mathematics achievement is needed to find effective means for producing adequate STEM-potential students. Additionally, a useful empirical perspective and deeper understanding of mathematics performance predictors can be provided by conducting a cross-national comparative study. Therefore, the present study attempts to contribute to the development of policies and strategies for improving mathematics achievement and suggest new perspectives.

Statement of Problem

Strategies for improving mathematics performance are needed since U.S students continue to lag behind other industrialized countries. Earlier studies on students' mathematics achievement, limited research on exploring factors that are associated with mathematics achievement because those studies have generally focused on single-level factors. For example, the most common predictors of mathematics achievements are demographic characteristics of students such as gender, race, and SES (Galindo & Sonnenschein, 2015; Barr, 2015; Cheema & Galluzzo, 2013; Sonnenschein & Galindo, 2015; Royer & Walles, 2007) and non-cognitive characteristics such as interest, attitude, anxiety, motivation, and self-concept (Semeraro et al., 2020; Lee & Shute, 2010; Aksu & Guzeller, 2016). Other math achievement-related factors from a teacher, school, and country have been explored in previous studies. Teacher-related factors include the teacher's gender, educational level, teaching experience, professional qualification, and teacher job satisfaction (Banerjee et al., 2017; Haider & Hussain, 2014). School location, school, and class size, school climate, and types of school have been investigated as school-related factors that are associated with students' achievement (Pong & Pallas, 2001; Neal 1997; Bernardo et al., 2015).

Although many researchers have investigated factors related to mathematics achievement, studies that used multilevel approaches are relatively few. Students are influenced by various surrounding characteristics because learning occurs in diverse contextual settings not in individuals. Inevitably, people are influenced by other people who are near them and by their surroundings including their teacher, school, state or province, and country. In addition, adolescence is a sensitive and vulnerable period, so adolescents are easily influenced by their surrounding environments (Gwon & Jeong, 2018) and these may influence their attitude toward learning and their academic performance. Since students spend a lot of time in school: U.S. students in public school the average number of hours in the school day is 6.64 hours (Tourkin et al., 2007), students are influenced by various school contexts and practices. Therefore, students' surrounding effects need to be examined to explore factors that influence their academic performance more accurately. In other words, schooling activities occur within hierarchical structures since students learn in classrooms located within schools, within school districts, within countries, and so on. Therefore, researchers should consider the hierarchical structures of educational data.

Moreover, the ecological fallacy can occur when researchers ignore the hierarchical characteristics of the data. The ecological fallacy refers to “errors committed by taking a relation between variables established at one level and transferring it to different level without checking its validity” (Snijders & Bosker, 2011, p. 70). In other words, the ecological fallacy means interpreting aggregated level’s results at the individual level or vice versa. Many studies have committed ecological fallacies by ignoring the discrepancy between the ecological level and the individual level. Consequently, interpreting aggregated data may lead to an ecological fallacy and undermine the conclusions of a causal relationship between variables. Therefore, researchers should design their studies at the appropriate unit of analysis to avoid leading ecological fallacy. Students are influenced by factors at different levels. For example, students are influenced by classrooms and teachers who manage the classrooms, schools, districts, and provinces. Since school hierarchical layers affect the student's academic achievement through direct and indirect cross-level effects, multilevel analysis is appropriate to investigate factors that are associated with student outcomes.

While some studies have been conducted to investigate the effects of students' surrounding environment on their' achievement, most of them are about investigating and identifying school effects. School effect refers to the effect on an outcome of a certain practice or policy or the extent to which attending a specific school affects a student's outcome (Raudenbush & Willms, 1995). However, broader environmental factors should be considered since schools interact with those social and physical surroundings. One of the limitations of multilevel studies in educational research is that those studies usually focus on the multilevel structure of students nested within schools, which is a two-level model. The two-level model may not be enough for significant analysis when researchers encounter complex hierarchically nested data structures. Student outcomes are predicted not only by level 1 and level 2 but by level 3 and even level 4 as well. For example, a three-level model is needed when we analyze data that have nested structures such as students nested in teachers, and teachers nested in school. Therefore, analyzing hierarchical data structure with more than 2-levels through the multilevel model is needed to get increased accuracy of the estimated coefficients and more interpretable results by allowing predictors to be considered at different levels.

Also, findings from cross-national studies can provide meaningful implications for mathematics education in the United States. If we find powerful predictors or patterns regarding cross-national variability in mathematics achievement, the practical implication can be provided. The core methodological strength of multilevel theory in education is that how individual factors influence student achievement is conditional on country-level context. For example, country-level predictors such as the wealth of the nation, gender inequality, or culture may be significantly related to individual student achievement. Further, the effects of student-level variables and school-level variables may differ depending on countries.

While numerous studies have investigated factors that influence students' mathematics achievement through multilevel modeling, few studies have analyzed country effects of individual math achievement. In educational research, cross-national studies are mostly conducted by comparing countries' differences in effects on academic achievement. However, multilevel models with country-level predictors in cross-national research are crucial in social science research because comparing individuals across country contexts can get how social, economic, cultural, and institutional contexts are associated with individual outcomes (Giesselmann & Schmidt-Catran, 2019). Considering multilevel analysis is important since although many studies have investigated the relationships between various predictor variables and the student outcome variable from within-country analysis, the relationships do not hold at the cross-national level. To avoid inferential error by analyzing only single-level data, the data have multilevel structures including student, school, and country-level need to be recognized and analyzed for the cross-national study.

Purpose of the Study

The first goal of the study is to conduct contextual analysis to explore the effects of the national and cultural contexts on students' mathematics achievement. Exploring country-level factors that contribute to the variation has been largely ignored in educational studies due to a lack of country-level data. Accordingly, studies investigating students' academic achievement heavily focus on the individual- and school-level factors. Studies without considering the effects of country-level determinants can make mixed results and these studies cannot capture social forces that can enhance or aggravate student achievement. Developing more broad understanding of phenomena by considering country effects may help us find important factors that were missed in other studies. To explore micro and macro effects on students' mathematics achievement, conducting multilevel modeling with country-level variables is needed.

The second purpose of the study is to investigate the nature and magnitude of student-level, school-level, and country-level factors that are associated with math achievement by using multilevel modeling, which is also called hierarchical linear modeling (HLM). Numerous studies have found which student-level individual factors explain student mathematics achievement, but the magnitude of the associations varies according to other contextual factors. Therefore, a multilevel analysis should be considered to find the factors that are still associated with math achievement after controlling for student-level variables. Group contextual effects such as school effects and country effects on individual math achievement can be estimated through HLM while those cannot be estimated through a single-level analysis.

Since this study hypothesized that national and cultural characteristics are associated with math achievement, this study especially focused on the effects of the country's university admission procedure and the country's culture of mindsets about intelligence on the country's math achievement among country-level predictors. Also, this study hypothesized that providing extra-curricular activities in school is associated with math achievement. Accordingly, the variable indicating extra-curricular activities in school was selected as the main interest in the study. This study tried to examine the relationship between student-level predictors and math achievement, and the main student-level predictors were focused on were students' mindsets about intelligence and information and resilience self-efficacy. The specific research questions are presented in the following:

1. Is there significant variability in mathematics achievement across schools and countries? If so, how will total variation be allocated to student-, school-, and country-level?
2. How are country-level variables associated with the country-mean student's mathematics achievement? Do the type of country's university admission procedure and country's culture of mindsets about intelligence significantly predict the country-mean student mathematics achievement?
3. How are school-level variables associated with school-mean student mathematics achievement? Do extra-curricular activities in school significantly predict the school-mean student mathematics achievement?
4. How are student-level variables associated with the student's mathematics achievement? Do student’s ICT usage, growth mindset, and resilience self-efficacy usage significantly predict the student's mathematics achievement?
5. Are there any school-level and country-level compositional factors strongly associated with mathematics achievement?

Conceptual Framework

The theoretical framework of this study is built on the multilevel paradigm. The development of multilevel analysis (Bryk & Raudenbush, 1992) and multilevel analysis software have promoted a multilevel paradigm in educational research. According to Dunn et al. (2014), "Multilevel theories explain individual or group processes and outcomes in terms of the multiple contexts in which these experiences occur. Conceptually, these frameworks examine one or more systems or environments" (p.3). Since multilevel data should be explained by multilevel theories, researchers must define which direct effects and cross-level interaction effects can be expected in their studies by articulating specific theoretical models (Hox & Van, 2017).

A cross-national study will be conducted in this study. Therefore, the study requires cross-level theorizing by identifying country-level characteristics that are associated with an individual- or group-level response (Tsui et al., 2007). This study will apply the cross-level direct effects model (Klein & Kozlowski, 2000) as a dominant theoretical framework. The cross-level direct effects model considers that "a predictor variable at one level of analysis influences an outcome variable at a different -typically lower-level of analysis (Klein & Kozlowski, 2000, p.218). The study hypothesized that higher-level factors including country- and school-level have a direct effect on student mathematics achievement.

The hypothesis that country characteristics influence student achievement is underpinned by social cognitive theory (Bandura, 1986) and sociocultural theory (Vygotsky, 1978). Bandura's social cognitive theory stresses that learning occurs in social contexts with the interaction between personal factors and behavior (Bandura, 1986). Vygotsky's sociocultural theory emphasizes the influence of social interaction and culture in learning. According to sociocultural theory, culture is the primary determinant of knowledge acquisition and the development of higher psychological functions (Vygotsky, 1978). He asserted that "Every function in the child's cultural development appears twice: first, on the social level, and later, on the individual level; first between people (interpsychological) and then inside the child (intrapsychological)" (Vygotsky, 1978, p. 57). Underpinned by both theories, this study hypothesized that mathematics achievement is influenced by not only individual characteristics but also environmental contexts.

The conceptual framework of this study focuses on the impacts that different levels of social organizations may have on a student's mathematics achievement. The three-level hierarchical linear model (HLM) will be used to decompose total variance into students (Level-1), across, across schools (Level-2), and across countries (Level-3) and then account for the variation at each level by two corresponding level variables that represent certain characteristics of the organizations. The results of the study will reveal how many variances at level 1, level 2, and level 3 and estimate the associations of each group-level predictor with the outcome. Student-level (Level-1) variables include gender, parental education level, information, and communication technology (ICT) usage, perceived parents' emotional support, sense of belonging in school, resilience self-efficacy, mastery goal orientation, fear of failure, occupational aspiration, belief in the value of school, and growth mindsets. As school-level (Level-2) variables, school locale, type of school, student-teacher ratio, class size, the proportion of fully certified teachers, class size, extra-curricular activities in school, student behavior hindering learning, and teacher behavior hindering learning. For country-level (Level-3) variables, OECD members, the university admission procedure, gross domestic product (GDP) per capita, gender inequality, and the GINI index were included.

Characteristics of the dataset

The study used the dataset from the PISA, the Program for International Student Assessment, which is an international assessment that was established by the OECD in 1997. The main purpose of the PISA is to measure 15 years old (seventh grade and above) students' performance in reading, mathematics, and science. Also, it collects data from responses from school principals, teachers, and parents. The first PISA test was published in 2000 and the dataset of the test has been provided every three years.

The PISA 2018 data that will be used in this study among PISA results were published. 79 countries participated in the PISA 2018 assessment and most countries assessed between 4,000 to 8,000 students who were randomly selected from at least 150 schools. Therefore, about 600,000 students from 79 countries participated in the test. Among 79 countries that participated in PISA 2018, 37 countries are members of the OECD while 42 countries and economies are non-OECD members. Reading, science, and mathematics literacy were tested. Also, background questionnaires and non-cognitive variables were answered by students, students' families, teachers, and school principals. In this study, mathematics literacy results and variables from students' and schools' questionnaires in PISA 2018 will be used as student- and school-level variables. For country-level variables, data from various global reports will be used.

Significance of This Study

The findings of this study can contribute to the literature in the following ways. First, the findings of this study can help to understand factors that predict students' mathematics achievement. Since improving student academic achievement is the central goal of the school system, providing empirical evidence supports the assertion that approaches and strategies should be adopted for improving students' math achievement. As mentioned earlier, countries with a large proportion of students with higher levels in mathematics show higher economic growth, factors that are mainly associated with mathematics achievement are needed to be explored for increasing the countries' talent pools in STEM. Especially, this study focused on specific variables at the student, school, and country levels and math achievement. At the school-level, students' ICT usage, growth mindsets, and resilience self-efficacy are the main interest. At the school-level, the student-teacher ratio and extra-curricular activities in school are the main interest. At the country-level, university admission procedure and the country's culture of mindsets about intelligence. A major strength of this study is that we can examine the effects of these three predictors controlling for other various student-, school-, and country-level variables.

Second, providing cross-national comparisons of different contextual factors that are associated with mathematics achievement may provide benchmarks of how the United States differs from or is like other countries. Accordingly, useful information can be discovered by comparing mathematics achievement among diverse countries. Conducting cross-national studies and being aware of issues in other countries are effective ways to find improvements in education systems, qualities, or policies. The study may lead researchers and policymakers to find why and where US students are lagging behind and let them explore whether or not there are any educational policy implications for students' mathematics performance enhancement in the United States. Since adolescents in the United States continue to lag behind their peers in East Asia and Europe in mathematics, exploring key differences in how other countries educate students is needed to analyze to find key predictors of math achievement in different countries. Therefore, the country-level differences and factors that explain the differences should be examined in this study.

Third, educational research using the three-level HLM model is relatively fewer than other models due to the limitations of the available dataset. According to Maas and Hox (2005), samples with more than 50 macro units can make unbiased estimators in a multilevel model. Therefore, conducting multilevel analysis including country-level predictors is demanding more than 50 countries' datasets. Since this study used 58 countries' datasets, the country-level sample size is sufficient to reliably estimates effects by using HLM analyses.

Lastly, ecological fallacy can be avoided in this study. Usually, researchers analyze multilevel data such as students nested within schools. Also, many researchers have often overlooked ecological fallacy when they apply country-level variables in multilevel analysis. Some studies assume that the group-level and the individual-level relationships are equal, but this assumption is not appropriate since group-level phenomena are not simple aggregations of individual levels. For example, May et al. (2003) found from TIMSS data the results of the relationship between predictor variables and the outcome variable at the student level and the country-level were opposite. These results indicate that the interpretation of relationships for the same variable might be different in different contexts. Therefore, avoiding ecological fallacy by using multilevel modeling procedures is needed.

Chapter 2 Literature Review

The second chapter explores the theoretical literature and empirical research on mathematics achievement and the factors that contribute to higher levels of achievement in mathematics. The first section of this study describes the importance of mathematics achievement. The second section presents the literature review following the hierarchical structure that is used for analyzing the data that was used in this study. As such, the literature review focuses on the student-level (level 1) factors that affect students' mathematics achievement are described in the second section. The third section introduces the literature review that focuses on the school-level (level 2) and lastly, country-level (level 3) predictors that are associated with academic achievement that appeared in the literature.

Importance of Mathematics Achievement

Mathematical knowledge is "a powerful vehicle for social access and social mobility. Hence, lack of access to mathematics is a barrier - a barrier that leaves people socially and economically disenfranchised" (Schoenfeld, 2004, p.255). Therefore, the successful teaching and learning of mathematics play an important role in the national prosperous future. Mathematics is critical in enabling students to understand other school subjects such as science, social studies, and even music and art (Ali & Jameel, 2016). Mathematics plays a fundamental role in the fields of science and technology (Fatima, 2012). Accordingly, mathematics education is crucial to foster students' positive STEM identities and success in educational environments and future careers. Further, mathematical knowledge is crucial for students' critical thinking and communication skills using mathematical logic (Schoenfeld, 2002).

As mentioned in the introduction, the middle school years are a particularly important period of mathematics education. Eighth-grade mathematics is an important step in advancing mathematics learning since mathematics courses are sequenced and these sequences become solidified in eighth-grade mathematics learning (Wang & Goldschmidt, 2003). Students start learning algebra usually from ninth grade and algebra is critical for future employment opportunities not only in STEM-oriented careers but also in jobs considered to be blue-collar because it can develop problem-solving and critical thinking skills (EdSource, 2009). Moreover, early mathematics knowledge can predict students' later reading achievement since mathematical thinking is associated with cognitive development (Clements & Sarama, 2016).

Poor performance in mathematics may increase math anxiety, and it also may increase avoidance of and underperformance in STEM domains (Daker et al., 2021). There are diverse factors that are associated with poor performance in mathematics. Low mathematics self-efficacy, which refers to individuals' self-belief in their ability in mathematics, negatively influences overall academic performance (Lin, Lee & Snyder, 2018). Also, a negative attitude toward mathematics teachers and school environments may cause low mathematics achievement. According to Jameel and Ali (2016), teachers who are using less interesting methods of instruction could negatively influence students' understanding of mathematics. Zedan and Bitar (2014) found that class climate such as a feeling of calm, motivation, satisfaction, and enjoyment are associated with students' self-efficacy and achievement in mathematics. These findings suggest that a negative class climate may negatively affect students' mathematics achievement.

Predictors of Low mathematics achievement in the U.S

Many reports are showing that the United States lags behind other countries in mathematics, but studies investigating reasons for that are few. One of the possible reasons why students in the United States are falling behind is cultural differences. Some previous studies have investigated the differences and similarities between East Asia countries and Western countries. One major difference is Confucianism in East Asia countries. Leung (2001) argued that students in East Asian countries have better achievement in mathematics because those countries are part of the Confucian heritage cultures (CHC), which can be described as cultural communities that share the values of Confucianism. Confucius viewed the purpose of learning as to improve one's character and conduct self-cultivation, and finally become a superior person who has high moral virtue (Ng, 2009). In addition, CHC countries believe that studying and learning are hardships, not enjoyable experiences (Leung, 1998). Therefore, parents and teachers in those countries attach importance to achieving high academic achievement and having high academic expectations for students (Sollenberger, 1968). Accordingly, people in countries under the influence of Confucianism including China, Taiwan, Korea, Japan, and Singapore consider education as the most viable and valuable way to achieve personal and social success. For example, people in South Korea view obtaining higher education as one of their most important priorities and believe they can accomplish desired economic and social goals if they achieve a high level of education (Kim & Park, 2000). According to PISA 2019 results, countries with Confucian heritage culture ranked in the top ten in mathematics performance (China ranked first, Singapore ranked second, Japan ranked sixth, and South Korea ranked seventh).

Second, the low investment in preschool education in the United States might be a cause of low mathematics performance. The report from the Center for American Progress argued that the United States should invest more in preschool and enhance preschool enrollment to succeed in mathematics in secondary school (Herman et al., 2013). According to Cooper and Costa (2012), there has been a lack of investment in preschool education compared to other countries. They noted that only 0.4 percent of the U.S. GDP is allocated to public and private preschools while other countries spend more than that. For example, OECD countries spend over 0.7 percent of their GNP on preschool and Nordic countries including Sweden, Iceland, and Norway spend higher than 1.0 percent of GDP on preschool education (Organisation for Economic Co-operation and Development, 2011). Early childhood education is crucial to improve students' later mathematics performance. The researchers found from the longitudinal study that mathematics achievement in early childhood significantly predicts math achievement in secondary school (Geary et al., 2013). The authors noted that one in five adults in the United States is functionally innumerate which means that they cannot solve eighth-grade mathematical problems, and the findings from the study early instruction may implicate early instruction of numeracy skills can improve students' long-term mathematical competence.

Third, unbalanced curriculums can explain poor performance in mathematics for students in the United States. Ravitch and Cortese (2009) found that high-performance countries have a more balanced curriculum and time allocation for subjects than the OECD average. The authors stated, "high-performing countries seem to devote significant effort and resources to maintaining a broad, comprehensive core curriculum" (p.83). According to PISA data, instructional time in mathematics does not significantly predict students' improvement in mathematics. Instead, a balanced curriculum approach might be an important predictor of mathematics achievement. For example, high-performing countries in mathematics such as Japan and South Korea have a slightly less concentrated curriculum in mathematics than the OECD's average. For example, Mathematics comprises a 16 percent share in Japan and a 14 percent share in South Korea while a 17 percent share at the OECD level (All, 2019).

All fifty states have their own curriculum, funding, tests, and standards. Even the United States Department of Education is providing national standards but has no power over state authority. Accordingly, teachers are relatively flexible on instructional plans and students are free to organize their learning. Since most high-performing countries such as Japan, South Korea, Switzerland, and New Zealand have their national curriculums which have particular goals, values, and content standards. Establishing a national standard curriculum in the United States can be positively correlated with students' mathematics achievement since the United States is on the opposite track of other industrialized countries. According to Stigler et al. (1982), the mathematics curricula of Japan contained detailed concepts, and textbooks were all based on the national curriculum that was defined by the Ministry of Education while there was a big variation of textbooks in the United States, and the researchers found that children from Japan consistently achieved higher performance in mathematics than their counterparts in the United States. Some argued that implementing a national curriculum may improve the equality between advantaged and disadvantaged school districts and enhance overall school quality (Nerison-Low & Ashwill, 1999; Johnson, 1986).

Lastly, U.S students have experienced the challenge of educational equity in mathematics. Although national organizations including the Association of Mathematics Teacher Educators (AMTE), the National Council of Supervisors of Mathematics (NCSM), and the National Council of Teachers of Mathematics (NCTM) are supporting educators and teachers to build equity in mathematics education (Gutiérrez et al., 2008), achieving equity in mathematics in schools is very difficult in the U.S. According to Lubienski (2002), education researchers in the U.S have given little attention to students' cultural backgrounds about mathematics learning. Also, the results of the meta-analysis that was conducted by using data from the National Assessment of Educational Progress (NAEP) from 1990 to 2011 showed that there were stable gender gaps in mathematics and science achievement for students in the U.S (Reilly et al., 2015). William's study (2012) showed that the gap in mathematics achievements differs across racial/ethnic groups as well as different socioeconomic groups, which is that African American students who are in lower socioeconomic groups are the most vulnerable to mathematics achievement. Furthermore, there is a persistent disparity in academic achievement across states. According to NAEP 2019, Alabama and New Mexico had the lowest eighth graders' scores in mathematics, which was 12 points lower than the national average score of 281. Other states that scored lower than the national average were Kentucky, Delaware, Oklahoma, South Carolina, Rhode Island, California, Hawaii, Arkansas, Nevada, Mississippi, West Virginia, and Louisiana while the states that scored higher than the national average were New Jersey, Minnesota, Wisconsin, New Hampshire, South Dakota, Pennsylvania, Nebraska, Utah, Colorado, Montana, and North Carolina. Underperforming states were mostly located in the south or the southwest areas. Achievement gaps between races and states have not been significantly narrowed. Hansen et al. (2018) noted that only fewer than half of all states have made a substantial stride in narrowing achievement gaps and the authors stated that "Unless we rapidly increase the rates at which we close our race-, ethnicity-, and income-based gaps, unequal access to education and the consequences of this inequality will affect students today as well as subsequent generations" (para. 15). The No Child Left Behind Act (NCLB) has been implemented in the United States since 2001 (US Department of Education, 2001) to narrow the achievement gap among students, but it has done little to reduce the gap (Eskelsen & Thornton, 2015).

Student Level Characteristics

Compared to the classroom, and school factors, the influential factors associated with a student's academic achievement are the individual's background and characteristics. Numerous studies have examined how much variance in students' achievement is explained by the difference between students and the percentage of variance differs depending on research purpose and methods, but it varies between 70 percent and 95 percent (Hermans et al., 2017). Therefore, exploring student-level characteristics is crucial to understand the factors affecting mathematics achievement.

Gender

Within the field of mathematics education research, the debate over gender differences in mathematics performance has continued throughout the decades. The results from U.S. national and international surveys show that boys tend to outperform girls in mathematics. Among SAT and ACT, which are both standardized tests used for college admission in the United States, boys outnumbered by a ratio of 4:1 and 3:1 in the top 0.01 % of the distribution for the mathematics test of the SAT and ACT between the years 2006 and 2010 (Wang & Degol, 2017). According to the results of PISA 2018, male students outperform female students in mathematics in most OECD countries except Finland, Greece, Iceland, Israel, Lithuania, Norway, and Sweden (Peña-López, 2019).

Some have suggested that males and females differ in their mathematical ability due to biological differences (Benbow. 1988; Halpern et al., 2005). According to a study by Levy and Kimura (2009), females have little advantage over males in mathematical calcualtion, while males do better in problem-solving using mathematical reasoning due to biological differences. According to another strand of research, gender differences in mathematics performance may be due to societal factors. Nollenberger et al. (2016) asserted that cultural attitudes toward women determine gender gaps in mathematics performance. Beliefs that mathematics is masculine discipline and expectations of parents and teachers who encourage male students to achieve in mathematics more than female students cause gender differences in mathematics (Jacobs et al., 2005).

On the other hand, some have argued that there is no significant gender difference in mathematics performance. According to Kersey et al. (2019), males and females engage in the same neural functions during mathematics development. Meta-analysis findings between 1990 and 2007 remarked that gender differences in mathematics performance were trivial Cohen's $d= .05$, indicating no gender difference, and VR (the variance ratio) =1.08, indicating almost equal male and female variances (Lindberg et al., 2010). In addition, a study examined gender differences among U.S students' by using longitudinal multilevel modeling and found that both male and female students showed the same growth trend in mathematics performance and females even have a higher mathematics GPA than males from middle school to high school transition (Ding et al., 2006).

Parental characteristics

There are various definitions of parental characteristics. Some researchers define parental characteristics as demographic aspects such as their age, race, educational level, employment status, and SES backgrounds (Gau et al., 2008; Ishizawa & Kubo, 2014; Hsieh & Shen, 2000). On the other hand, some other researchers have defined parental characteristics as psychological and behavioral factors. According to Carranza et al. (2009), psychological control, parental competency, and love inconsistency were considered parental characteristics.

Researchers in education have long been interested in the association between parental characteristics and students' academic achievement. Many studies have examined direct and indirect relationships between parental characteristics and mathematics achievement. Shoraka et al. (2015) showed that parental education and occupation predict student mathematics achievement among students in grades 7 to 9. Rodríguez et al. (2017) found that parents' expectations are positively related to students' mathematics achievement, and this relationship is mediated by students' self-efficacy. Also, parental academic support and emotional support are significant predictors of adolescents' academic achievement (Wentzel et al., 2016; Aman et al., 2019). Additionally, a study found that parents' SES has a positive effect on mathematics achievement, and is mediated by parental involvement (Yıldırım, 2019).

Socioeconomic status (SES)

The relationship between math achievement and socioeconomic status (SES) has been widely studied. Sirin (2005) stated, "SES is the most widely used contextual variable in education research" (p.417). Villalba (2014) defined SES as "A construct that represents the social and economic background of an individual or group unit". There are a variety of ways of measuring SES. Jeynes (2002) describes that SES is measured by three major components including family income, parental education, and parental occupation. In the United States, free/reduced lunch also has been widely used to measure SES (Nicholson et al., 2014; Harwell et al., 2004). The results of the meta-analysis discovered that there is a medium to strong relation between SES and academic achievement, but the SES-achievement relation is moderated by characteristics of variables that are used to measure SES and student characteristics (Sirin, 2005). There is a significant gap in math performance between low-SES students and high-SES students when they enter school, and this gap does not shrink over the course of the school year (Duncan & Magnuson, 2011). Some studies found from a multilevel analysis that both student and school SES affect mathematics achievement among middle school students (Takashiro, 2017).

Information and Communication Technology (ICT)

Information and Communication Technology (ICT) refers to "technologies that provide access to information through telecommunications. It is similar to Information Technology (IT) but focuses primarily on communication technologies" (Ratheeswari, 2018, p.45). ICT is a broad subject, and the concepts are expanding with the development of technologies. ICT includes computers, software, the Internet, and portable electronic devices such as smartphones, laptops, and tablet computers. Especially, accessing the Internet by using mobile devices can increase opportunities for students to get high-quality learning experiences and resources. In PISA 2018, ICT resources were specified as smartphones, computers (including desktop computers and portable laptops), tablet computers, and E-book readers.

In education, ICT plays an important role in students' academic outcomes. Students can learn more efficiently by using it. Also, many works of literature argued that ICT can be used as an important tool to improve students' learning skills and increase the motivation of low-achieving students. Escueta et al. (2017) described that ICT such as educational software show "enormous promise in improving learning outcomes, particularly when it comes to mathematics" (p.22). According to Ishaq et al. (2020), ICT had a significantly positive impact on students' academic performance because students improve their learning capabilities and expand their memory by using ICT tools, such as laptops and personal computers. Suleman et al. (2017) conducted a pretest-posttest quasi-experimental study and found that there is a positive link between the use of ICT in teaching and learning and students' achievement in science. Also, Mullamaa (2010) claimed that ICT tools can be used for supporting student-centered learning and improving student motivation. On the other hand, Zhang and Liu (2016) found a negative relationship between ICT use and student achievement in mathematics and science.

Non-Cognitive Predictors

Non-cognitive predictors have been considered important in explaining academic outcomes. The term "non-cognitive" refers to a set of personal attributes, behaviors, skills, and characteristics representing one's psychosocial dispositions such as motivation, self-esteem, attitude, emotion, and so on (Gutman & Schoon, 2013). Non-cognitive abilities are different from cognitive abilities since cognitive abilities are related to brain-based skills requiring the acquisition of knowledge such as thinking, reasoning, or remembering (Kiely, 2014). There have been many recommendations about important non-cognitive predictors that are significantly associated with students' academic achievement. Non-cognitive predictors include personal and social dimensions, adjustment, motivation, and student perceptions (Sedlacek, 2017). Numerous non-cognitive factors have been found in previous studies. According to Hattie's meta-analyses of the contribution to students' mathematics achievement, cognitive constructs that are significantly related to math achievement are engagement, motivation, self-concept, and attitude toward mathematics (Hattie, 2008). Another study found from PISA and TIMSS that self-belief, self-efficacy, confidence, and educational aspiration are the best factors that predict student achievement in mathematics (Lee & Stankov, 2018). In addition, Beckmann and Minnaert (2018) found that negative emotions such as fear of failure, emotional issues or instability, feelings of stress and tension, and feelings of frustration are important non-cognitive characteristics of students.

One of the most important non-cognitive predictors of students' academic outcomes is self-efficacy. Self-efficacy is defined as the "belief in one's capabilities to organize and execute the courses of action required to produce given attainments." (Bandura, 1997. p.3). According to Bandura (1997), individuals act when they have efficacy beliefs and outcome expectations that their actions and effort will produce desired outcomes. Therefore, self-efficacy reflects confidence in one's ability to succeed in specific situations or tasks. Students who have stronger perceived learning self-efficacy are more likely to try hard and complete academic tasks. Perceived self-efficacy plays an important role in social cognitive theory since self-efficacy beliefs influence individuals' aspirations, strategic thinking, motivation, and resilience (Bandura et al., 2001). Many studies have shown that self-efficacy is a key predictor of students' academic achievement. Komarraju and Nadler (2013) asserted that students who have high levels of self-efficacy for academic learning are more likely to achieve academic success because they self-regulate and monitor their impulses and endure difficulties. According to findings from the study of Olivier et al. (2019), students' self-efficacy in mathematics contributed to their later achievement in math and long-lasting positive perceptions about themselves.

Mastery goal orientation and occupational aspirations are also non-cognitive predictors that are associated with student academic achievement. Goal orientation refers to the disposition to complete individual goal setting (Ames, 1992). The mastery goal orientation is one of three types of achievement goal orientation: mastery goal orientation, performance-approach goal orientation, and performance-avoidance goal orientation. Mastery goal orientation is referred to as having the goal of developing new skills, valuing the process of learning itself, focusing on better understanding, and enhancing competence (Ames & Archer, 1988). Performance-approach goal orientation is focusing on the need to demonstrate ability and performance-avoidance goal orientation is focusing on avoiding failure and hiding the lack of ability (Elliot, 1999). Many studies have shown that mastery goal orientation is regarded as desirable in achieving high academic performance. According to previous works of literature, mastery goals are positively associated with students' academic performance, expectation, and self-efficacy and negatively related to test anxiety (Dull et al., 2015; Ho & Hau, 2008). Also, mastery goal orientation is more consistent in learning than performance-approach goal orientation (Midgley et al., 2001). In the study of Keys et al. (2012), they examined the association between goal orientations and mathematics achievement and found that only a mastery goal orientation consistently predicted math achievement even after controlling for students' demographic characteristics.

Occupational aspirations are defined as "an individual's expressed career-related goals or choices" (Rojewski, 2005, p.132). In other words, occupational aspirations are the intention and preference to pursue specific career decisions. Occupational aspirations have been shown to play an important role in understanding adolescents' academic outcomes and future success. Since individuals start to consider their future careers and narrow their specific occupational choices during adolescence (Watson et al., 2002), adolescents' occupational aspirations may influence academic motivation and achievement. Previous studies have found that adolescents' occupational aspirations are important determinants of their future success. According to Cochran et al. (2011), adolescents' occupational aspirations are associated with career success in midlife. Also, findings of prior research (Zimmerman et al., 1992) indicated that individuals' aspirations play a role as an important mediating factor between self-efficacy and academic achievement.

Positive mindsets are non-cognitive factors closely related to academic performance. Students' sense of belonging in school is one of the academic mindsets and it has been proposed by many researchers as a means of increasing their learning. Sense of belonging in the school is "the extent to which they feel personally accepted, respected, included, and supported by others-especially teachers and other adults in the school social environment" (Goodenow & Grady, 1993, pp.60-61). They stated that a sense of belonging in school can be defined as the extent to which students feel about gaining acceptance, respect, inclusion, and support in the school. Sense of belonging in the school has been proposed by many researchers and teachers as a significant predictor of academic achievement. Students with a higher sense of belonging in school show higher academic achievement, intrinsic motivation, and positive attitudes regarding school (Chiu et al., 2016). According to Sirin and Rogers-Sirin (2004), the strongest predictors of academic performance were the sense of belonging in the school and educational expectations among African American students. Also, a longitudinal study found that school belonging was an important predictor related to a higher level of academic motivation over the four years of high school (Neel & Fuligni, 2013). Keys and Fernandes (1994) argued that school management is essential for students' success in school since a positive belief in the belief in the value of school and schoolwork was associated with a positive attitude toward school among secondary school students.

Growth Mindset

A growth mindset also has been used in several studies exploring the relation with academic achievement. Certain students believe that their intelligence is a fixed trait while others believe that their intelligence can be increased with effort. Dweck (1999) coined the term "fixed mindset" and "growth mindset". A fixed mindset indicates a belief that people are born with certain unchanging intelligence and ability, while a growth mindset is a belief that people's intelligence and ability can be developed with their effort. Dweck stated, "children with the fixed mindset — the ones who believed in fixed traits— stuck with the safe one…Children with growth mindset— the ones who believed you could get smarter—...They chose one hard one after another" (Dweck, 2008, p.13). Mindset and self-efficacy share some commonalities, but those two concepts are different. The main difference is that mindsets reflect an individual's belief in his/her intelligence while self-efficacy reflects an individual's perspective on whether he or she has abilities to complete a specific task or goal. Recent studies have investigated the relationship between mindsets and STEM learning. Particularly, several studies have focused on exploring variables that can mitigate historical and cultural stereotypes of underperformance in STEM fields. For example, there are stereotypes related to mathematics such as "math is a masculine domain" and "Asian people are good at math". A growth mindset has been claimed as a key variable contributing increase in academic performance, especially for youth influenced by those stereotypes (Aronson et al., 1999; Good et al. 2003). Accordingly, PISA included a "growth mindset" instrument in PISA 2018 for the first time to broaden the approach to students' learning and explore critical predictors for educational success (OECD, 2021).

Numerous studies have shown that a growth mindset plays an important role in educational experiences. According to a longitudinal study by Blackwell et al. (2007), students with growth mindsets were more likely to pursue their learning goals compared to those with fixed mindsets. In addition, several studies found that a growth mindset positively predicted self-efficacy while a fixed mindset negatively predicted self-efficacy (Young & Urdan, 1993; Bråten & Strømsø, 2005). According to Samuel and Warner (2021), university students with growth mindsets show higher math self-efficacy and lower math anxiety than students with fixed mindsets

PISA 2018 found that most students agreed with the growth mindsets statement in 52 countries and economies while most students agreed with the fixed mindset statement in 26 countries and economies. Also, PISA 2018 found that students who had a growth mindset scored 23 points higher in mathematics. Yeager et al. (2019) found that a growth mindset as a psychological intervention improved grades among lower-performing students and increased students' enrollment in advanced mathematics courses. Also, Claro et al. (2016) showed that a growth mindset can mitigate the negative effects of economic disadvantage on academic achievement. Despite numerous studies of the advantages of a growth mindset, there are continuous debates on mindsets. King and Trinidad (2021) argued that a growth mindset was only positively associated with academic achievement from higher SES families.

School Level Characteristics

A Series of studies have examined the school compositional effects on academic achievement in educational research fields. Dumay and Dupriez (2008) defined the school compositional effect as "the impact of pupil's aggregated characteristics when these variables have been taken into account at the individual level" (p.440). Investigating school compositional factors is important since the school compositional effect can explain significant proportions of between school's variance even after controlling for students' initial performance. Raudenbush and Willms (1995) distinguished the school compositional effect as Type A and Type B considering different uses of the school effect. Type A effects include the effects of school practice such as type of school, school location, school size, student-teacher ratio, teacher salary, and so on. Type B effects are isolated from the effects of a school's practice. Type B effects are correlated with students' family backgrounds such as SES, race, family type, and so on.

School locale

Numerous studies have investigated the effects of school locale such as urban, suburban, and rural classification on students' academic achievement (Xu, 2009; Alordiah et al., 2015; Murphy, 2019; Agbaje & Awodun, 2014). There are some debates on whether school location affects academic achievement or not. Some researchers in social science fields have contended that students in rural areas have lower academic achievement than their counterparts. Owoeye and Yara (2011) proved that students in urban schools achieved better academic performance than students in rural schools. In the study by Xu (2009), urban middle school students are more likely to be more self-motivated during their homework compared with their rural counterparts because students in rural schools place less importance on academics.

Type of School

The effects of school type on academic achievement have always held researchers' interest in social science. Schools are generally divided into two types: public and private. The majority of students attend public schools. Private schools include religious schools such as

Catholic, Buddhist, and Islamic schools. According to the results of PISA 2018, 82 percent of students attended a public school on average across OECD countries. According to the report from NCES (Wilkinson-Flicker, 2019), the U.S public K-12 enrollment is about 50.6 million while private school enrollment is about 5.7 million which means that about 90 percent of students attend public school in the United States.

There are conflicting results about the effects of school type on students' academic achievement. According to Neal (1997), there is strong evidence that attending Catholic school had a positive effect on academic achievement, especially for minority students. In addition, Bernardo et al. (2015) found that public school students had less school motivation compared to private school students and the motivation gap is related to the achievement gap. On the other hand, Newhouse and Beegle (2006) found that students who attended public secondary schools have high academic achievement compared to their counterparts who attend private schools after controlling for other characteristics. Also, Lubienski et al. (2008) argued that teacher certification and teaching practice are significantly correlated with student achievement and those are more prevalent in public schools than private schools.

School Climate

According to Cohen et al. (2009), School climate is "the quality and character of school life. School climate is based on patterns of people's experience of school life and reflects norms, goals, values, interpersonal relationships, teaching and learning practices, and organizational structures" (p.182). Adeyemi (2006) defined school climate as a set of unique features of a school that can affect the mood, motivation, creativity, and productivity of students and teachers. The National School Climate Center categorized school climate into five dimensions: Safety, Relationships, Teaching and Learning, Institutional Environment, and the School Improvement

Process (Thapa, 2013). According to National School Climate Center (2021), Safety is feeling safe in school socially, emotionally, intellectually, and physically and it is highly associated with fostering student's learning and well-being; Relationships refers to interactive respect for individual differences and supportive relationship with teachers and students; Teaching and Learning refer to providing supportive instructional practices to students in schools; Institutional environment includes school connectedness and engagement, physical surroundings, and social inclusion; the school improvement process.

Researchers and educators have recognized the importance of school climate for many years. A series of studies revealed that school climate is associated with academic achievement. Daily et al. (2019) found that the student-teacher relationship was the most significant predictor of academic achievement for middle school students among school climate domains while providing academic support was most significant for high school students. Also, Jones and Shindler (2016) explored the relationship between the school climate and student achievement by administrating the School Climate Assessment Instrument (SCAI) and found that the quality of school climate was highly correlated with academic achievement levels. According to Zysberg and Schwabsky (2021), interpersonal relations and a sense of belonging in the school among school climate subscales improve students' self-efficacy which lead positively correlates with their academic achievement. Vejian et al., (2016) stated that a school's creative climate can enhance students' creativity and develop their academic achievement.

Class size and Student-Teacher Ratio

Class size refers to the number of students in a class. Ehrenberg et al. (2001) argued that class size plays an important role in student learning since it can influence teacher behavior. Betts and Shkolnik (1999) found that teachers spend more time with students for reviewing their learning in smaller classes. The project was conducted by Mosteller (1995) to determine the effect of smaller class size and it was found that reducing class size from 22 to 15 increased both mathematics and reading test scores. Pate-Bain et al. (1992) argued that training teachers in small-group instruction is needed because reduced class size significantly improved student performance. On the other hand, a study concerned that reducing class size might cause a decrease in high-quality teachers (Mishel & Rothstein, 2002). Jepsen and Rivkin (2009) found that smaller class size increased mathematics and reading achievement but also increased in share of teachers lacking experience and full certification. A study examined the relationship between class size and mathematics achievement in nine countries including Australia, Canada, France, Germany, Hong Kong, Korea, Iceland, Singapore, and the United State, and found that only the United States had a negative association between math achievement and class size after controlling for the effects of teacher, school, and classroom variables, whereas other countries had a positive relationship. Student-teacher ratio (STR) is the number of students divided by the number of teachers in a school. STR and class size are highly correlated, but different since STR includes teachers in specialized roles who are not working as classroom teachers.

Certified Teacher

The relationship between teachers' certification status and student achievement has been heavily debated in educational research. Certified teachers refer to educators who achieved credentials from authoritative sources. According to PISA 2018 (OECD Publishing, 2020), "certified teachers are those licensed to teach in a school based on the standards defined by national or local institutions. The goal of teacher certification is to guarantee that schools are staffed with quality teachers" (p.92). Several studies showed that maintaining qualified teachers is the key determinant of teacher quality in improving student achievement. According to the report based on surveys of principals and teachers (Jelmberg, 1996), certified teachers received higher rates of instructional skills and instructional planning than alternative route teachers from their principals. Also, a study found that certified teachers produce higher student achievement than untrained teachers even after controlling for teacher experience, degree, and student characteristics. On the other hand, a study found that teacher qualification characteristics such as educational attainment or certification were not significantly associated with student achievement but years of teaching experience at a particular grade level had a significant association with higher achievement gain (Huang & Moon, 2009).

Holding an advanced degree among teachers has also been argued whether it is a significant predictor of student achievement. According to Goldhaber and Brewer (2000), there was a significant associated between a teacher with a master's degree and student mathematics achievement after controlling for student and teacher characteristics. Also, a study found evidence that having teachers with a master's degree was correlated with effectively improving student achievement in mathematics (Betts et al, 2003). On the other hand, Clotfelter et al. (2007) found that teachers who earned their master's degrees after five years of teaching are negatively correlated with student achievement.

Country level Characteristics

Gross Domestic Product (GDP) per capita

Education and economic development are closely related because countries can achieve sustainable development with investment in human capital (Ozturk, 2001). A country's economic power is linked to student achievement and there are many ways to estimate a country's economic power. Gross Domestic Product (GDP) is the most common and standardized measure of the size and health of a country's economy. GDP measures "the total value of all final goods and services that are newly produced within the borders of a country over the course of a year" (O'Neill, 2014).

According to Baker and LeTendre (2002), GDP per capita is a significant predictor of student academic achievement. Chiu (2007) described that students who live in countries with higher GDP per capita are likely to get more educational resources and learning opportunities. Accordingly, they have better academic performance in mathematics and science than those in less wealthy countries. Tucker-Drob et al. (2014) found that using data from the PISA 2005, the association between science interest and science achievement is stronger in countries with higher GDP, but the association between science interest and science achievement is low in countries with lower GDP. Dhanji (2012) made a comparison between developing countries and developed countries and found that GDP per capita significantly predicts students' academic performance in developing countries, but there is no significant association between GDP per capita and students' academic achievement in developed countries.

Gender Inequality

The relationship between the social status of women and academic achievement has been widely studied. As mentioned above, it has been generally documented that boys outperform girls in mathematics. Recent studies have focused on country characteristics such as culture, gender inequality, and multiculturalism for the reasons of the gender gap in math. Women's standing in society at a country level has been considered a contextual factor that contributes to student's academic achievement in mathematics.

According to Guiso et al. (2008), more gender-equal countries are associated with reducing the negative gap in mathematics achievement. Moreover, they found that females in more gender-equal countries show a larger positive gap in reading performance. These findings indicate that the gender gap in math has been eliminated in more gender-equal countries. Hannum (2005) showed that the gender gap in educational performance declines with social and economic development. According to Nollenberger et al. (2016), second-generation immigrant female students whose country of ancestry has a higher gender equality culture have narrowed the gender gap in mathematics. This can be interpreted as the student's academic performance being affected by their cultural background. On the other hand, Marks (2008) compared 31 countries by using the data from PISA 2000 and described that factor indicating gender inequality is significantly associated with the gender gap in reading but are not associated with the gender gaps in mathematics.

Income and Wealth Inequality

Every country has a range of SES levels, and the proportions vary from country to country. In the golden era of the U.S. economy, the quarter-century between 1948 and 1973, the benefits of education were shared among high-income and low-income families, but income gaps have sharply grown after the 1970s (Duncan & Murnane, 2014). Ever since then, the academic performances of U.S. students have continually declined and lagged behind those of students in other countries. In addition to country inequality, research is acknowledging the importance of studying country wealth inequality. While the concepts are similar, income and wealth inequality both have different properties. Income refers to an individual's remuneration for their work in a given year while wealth refers to the individual's total net worth (MasterClass, 2022).

Income and wealth inequality have been tied to various negative factors. According to Wolla and Sullivan (2017), both income and wealth are strongly related to the level of education. Contreras et al. (2015) conducted a cross-national study by using multilevel analysis and found that country's income inequality is significantly correlated with school violence which may affect negatively student academic achievement. Thorbecke and Charumilind (2002) described that income inequality may lead to disparity in educational attainments and opportunities and this consequently will exacerbate income and wealth inequality. Also, a study found that national wealth inequality is negatively correlated to school attendance by teenage boys (Esposito & Villaseñor, 2018).

University Admission Procedures

The college admission system is associated with not only secondary education but also primary education (Kang, 2006). The major screening factor in the college admission system is the college entrance exam. Most countries have standardized examinations for college admission, but the format, weight, and process of the examinations are different depending on countries. Some countries have national standardized college entrance exams and those exams play an important role in determining college acceptance. There are characteristics of the national standardized college entrance exams: the exams are only held once a year, the scores of the exams directly determine which universities students can go to, and the exams are held and managed by the government. For example, the National College Entrance Examination (NCEE), commonly known as the *gaoko* is held annually in China and students should get very high scores on that exam to enter prestigious universities (Zhang & Zhao, 2018). South Korea holds the College Scholastic Ability Test (CSAT), which is also known as *suneung*, once every year. The CSAT is the only national college entrance exam that is authorized by the government in South Korea. it is administered in paper-and-pencil format and the examination score is regarded as the most important factor for entering universities (Park, 2014).

On the other hand, some countries don't have national standardized college entrance exams. In the United States, students need to take the Scholastic Aptitude Test (SAT) or the American College Test (ACT) to apply to universities, but taking the tests is optional. Both tests are conducted by third parties, not by the government. Many universities in the United States do not require SAT or ACT scores for students and require their own admission criteria. In Australia, there is no national standardized college entrance exam. Instead, Australian states have their own university admissions requirements and exams, and each state calculates the Australian Tertiary Admission Rank (ATAR) score differently based on their criteria. Students can apply to universities with the ATAR score and the university's own criteria used for selecting students (Heck, 2021).

University admissions procedures vary from country to country and play an important role in understanding to what extent college admission characteristics influence student academic achievement. According to Lee (2018), types of college admission processes are associated with students' competition for entering universities and would influence parents' spending on shadow education such as private tutoring and cram school. Shadow education has been explained by experts as a predictor of the high academic achievement of East Asian students (Komatsu & Rappleye, 2018). Most East Asian universities' admissions are based on a high-stakes college entrance exam. Since a high-stakes college entrance exam is almost the sole determinant of college admission, the entrance exam is extraordinarily competitive and shadow education is prevalent in East Asian countries. For example, the participation rate of private tutoring from elementary to high school students in South Korea was 66.5% in 2020 (Korean National Statistical Office, 2021). In Japan, shadow education has a long history spanning decades and has been a major phenomenon (Sato, 2012). According to the report from the Ministry of

Education, Culture, Sports, Science, and Technology (MEXT, 2008), 51% of eighth grade and 65% of ninth-grade students attend *juku*, a system of private tuition in Japan. Also, the private tutoring market is $163 billion in 2021 and the participation rate of private tutoring from kindergarten to K-12 is about 50% in 2020 in China (Zheng et al., 2020).

Previous literature (Helms, 2009) has classified types of university admission procedures into five categories: 1) secondary leaving examinations; 2) entrance examinations; 3) standardized aptitude tests; 4) multiple examinations 5) no examinations. 'Secondary leaving examinations' indicate one of the university entrance systems that mainly rely on candidate students' scores on secondary school leaving examinations which generally were administrated by the government or schools. 'Entrance examinations' are the university admission system based on standardized tests that are administered by the national government or each university. 'Standardized aptitude tests' refer to examinations that are designed to evaluate students' cognitive abilities rather than their academic performances. 'Multiple examinations' indicate the university admission systems which consider secondary school leaving or university entrance examinations along with additional exams. The last type of university admission procedure is 'no examinations' which refers to the systems that do not require examinations but value candidate students' performance or experience during their secondary school.

Chapter 3 Methodology

Research Questions

Promoting high mathematics achievement is not only important for individual success but also it is crucial for national economic competitiveness. Since students are surrounded by multilevel contexts, students are influenced by a wide range of factors associated with students and their surroundings such as schools, and their countries. The main foci of this study are to investigate the relationship between mathematics achievement of 10th-grade students and variables each at the student, school, and country levels and examine whether the associations of variables of each level with mathematics achievement differ by country. This study will be guided by the following research questions, as stated in chapter one:

1. Is there significant variability in mathematics achievement across schools and countries? If so, how will total variation be allocated to student-, school-, and country-level?
2. How are country-level variables associated with the country-mean student's mathematics achievement? Do the type of country's university admission procedure and country's culture of mindsets about intelligence significantly predict the country-mean student mathematics achievement?
3. How are school-level variables associated with school-mean student mathematics achievement? Do extra-curricular activities in school significantly predict the school-mean student mathematics achievement?
4. How are student-level variables associated with the student's mathematics achievement? Do students' ICT usage, growth mindsets, and resilience self-efficacy usage significantly predict the student's mathematics achievement?
5. Are there any school-level and country-level compositional factors strongly associated with mathematics achievement?

Data Collection

The data used in this study is from the Programme for International Student Assessment (PISA) 2018. The first PISA test was published in 2000 and the dataset of the test has been provided every three years. The PISA assessment results have been published every three years since 2000, but the PISA 2021 has been postponed to 2022 due to the COVID-19 pandemic. The

PISA database provides data on 15-year-old (seventh grade and above) students' reading, mathematics, and science knowledge and skills. Also, it contains contextual information collected from students, their parents, teachers, and school principals. PISA 2018 consisted of a computer-based (Vietnam participated in PISA 2018 using a paper-based instrument) assessment of students and 79 countries participated and between about 4,000 to 8,000 students were randomly selected from at least 150 schools. Accordingly, 612,004 students from 79 countries participated in the test. According to the sample design, participating countries and economies were required to sample a minimum of 150 schools. The number of schools ranged between 44 to 1,089 and some countries did not meet the required number of schools: Brunei Darussalam (55), Luxembourg (44), Macao (45), Malta (50), Montenegro (61), North Macedonia (117), and Iceland (142). However, most countries and economies met the required minimum sample number. Among 79 participating countries and economies, 19 countries and economies additionally responded to the teacher questionnaire.

In this study, 58 countries were selected for analysis. Vietnam was removed from this analysis since Vietnam participated in PISA 2018 using paper-based instruments and key non-cognitive items were missed. Other 20 countries were removed from the analysis since those countries did not answer to items that were used as variables in this study. The countries that were analyzed in this study were listed in Table 3.1. The number of students ranges from 3,209 to 34,925 and the number of schools ranges from 48 to 825. As shown in the table, the average cluster size which can be obtained by dividing a student number into a school number is 38.58. The country had the smallest cluster size was Slovak Republic (17.40) and the country which has the biggest cluster size was Morocco (114.47).

Table 3. 1. *Countries Included in the Study*

Country	Country code	Number of Students	Number of Schools	Cluster size
Albania	8	6,188	118	52.44
Baku (Azerbaijan)	31	6,611	70	94.44
Argentina	32	1,1657	335	34.80
Australia	36	12,740	536	23.77
Bosnia and Herzegovina	70	6,383	139	45.92
Brazil	76	10,363	411	25.21
Bulgaria	100	5,148	160	32.18
Belarus	112	5,761	234	24.62
Chile	152	7,344	184	39.91
Chinese Taipei	158	7,154	164	43.62
Colombia	170	7,193	237	30.35
Costa Rica	188	7,166	204	35.13
Croatia	191	6,573	163	40.33
Czech Republic	203	6,845	306	22.37
Dominican Republic	214	5,525	178	31.04
Estonia	233	5,192	226	22.97
Finland	246	5,524	195	28.33
France	250	6,133	182	33.70
Georgia	268	5,486	308	17.81
Germany	276	4,481	169	26.51
Greece	300	6,370	209	30.48
Hong Kong	344	5,804	100	58.04
Iceland	352	3,209	112	28.65
Indonesia	360	12,019	276	43.55
Italy	380	11,439	443	25.82
Japan	392	6,015	183	32.87
Kazakhstan	398	19,441	595	32.67
Jordan	400	8,881	243	36.55
Korea	410	6,623	168	39.42
Malaysia	458	6,041	188	32.13
Malta	470	3,282	48	68.38
Mexico	484	6,465	251	25.76
Moldova	498	5,323	175	30.42
Montenegro	499	6,605	61	108.28

Morocco	504	6,639	58	114.47
Netherlands	528	4,623	131	35.29
New Zealand	554	5,839	173	33.75
Panama	591	6,057	157	38.58
Peru	604	6,045	330	18.32
Philippines	608	7,184	186	38.62
Poland	616	5,504	240	22.93
Qatar	634	13,457	184	73.14
Romania	642	5,057	142	35.61
Russian Federation	643	7,459	247	30.20
Saudi Arabia	682	6,059	87	69.64
Serbia	688	6,533	162	40.33
Singapore	702	6,633	158	41.98
Slovak Republic	703	5,882	338	17.40
Slovenia	705	6,323	303	20.87
Spain	724	34,925	825	42.33
Switzerland	756	5,618	203	27.67
Thailand	764	8,578	285	30.10
United Arab Emirates	784	18,759	582	32.23
Turkey	792	6,854	184	37.25
United Kingdom	826	12,391	294	42.15
United States	840	4,759	132	36.05
Uruguay	858	5,054	188	26.88
B-S-J-Z (China)	975	11,990	359	33.40
Total		455,206	13,519	

Note. B-S-J-Z (China) refers to four PISA-participating provinces/municipalities in China: Beijing, Shanghai, Jiangsu, and Zhejiang.

Sampling and Weighting

In this study, the target population was 15-year-old students attending educational institutions in grades 7 and higher, and schools from countries participating in PISA 2018. A simple random sample design was not used in PISA. Rather, a two-stage stratified cluster sampling design was applied in PISA 2018 to collect representative data from the target population efficiently. Stratified sampling refers to a method of sampling from a population that is divided into various subgroups (strata) sharing common characteristics (Acharya et al., 2013). The first-stage sampling units were composed of individual schools having students. Before selecting schools, stratification was used to make sampling more efficient. In PISA 2018, explicit and implicit stratification were used for school sampling. Explicit stratification refers to grouping schools into mutually exclusive strata. From each explicit stratum, an independent sample was selected. In other words, each participating country was divided into mutually exclusive groups, which also refer to explicit strata. Explicit strata were different across countries, but mostly region and school type were included as explicit stratification variables. Implicit stratification refers to sorting the schools within each explicit stratum by using implicit stratification variables. Examples of implicit stratification variables include the type of school, urbanization, school size, or school gender composition. Then, schools were selected through systematic probability proportional to size (PPS) sampling. PPS sampling is a sampling procedure under which the probability of a unit being selected is proportional to its size measure (Skinner, 2014). Therefore, larger clusters have a greater probability of selection and smaller clusters have a lower probability. The second stage sampling unit consisted of students within sampled schools. To be specific, 15-years students were randomly selected within every sampled school as a second stage sampling.

In this study, sampling weights were used to avoid sampling bias due to varying selection probabilities. Since PISA is a large-scale assessment, it may have an issue of sampling bias which means differences between the distribution of characteristics in the sample and the population (Arikan et al., 2020). Therefore, sampling weights should be applied to prevent the issue and make sure the sample is representative of the population. Sampling weights allow the analysis to reflect the population characteristics more correctly. Since this study conducted a multilevel analysis using a three-level model, data sets were weighted at the student level and school level. If sampling weights are ignored at either level, the parameter estimates can be biased. In PISA 2018 (OECD, n.d.), the final student weights can be expressed as

$$w_{ij} = \{[(w_{1i} * t_{1i}) * f_{1i}] * (w_{2ij} * f_{2ij})\} * t_{2ij}$$

with w_{ij} as the final student weight for student *j* in school i, w_{1i} as the school base weight for school i, t_{1i} as the school base weight trimming factors for reducing unexpectedly large values of w_{1i} , f_{1i} as the school non-participation adjustment, w_{2ij} as the within-school base weight of student *j* in school i, f_{2ij}as the student non-participation adjustment, t_{2ij} as the final factors for reducing the weights of students with exceptionally large values.

In this study, the Multicountry weight was used. According to Rutkowski et al (2013), the Multicountry weight is better than other types of weights for cross-country comparisons because it allows to calculate appropriate standard errors of parameters and obtain unbiased results. The Multicountry weight can be defined as

$$w_{ijk}^{*} = w_{ijk} \frac{\sum_{k=1}^{K} n_k}{\sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{i=1}^{n_j} w_{ijk}}$$

where K is the number of countries in the sample, *k* indicates the country, and n_k represents the sample size within country *k*. The sum of Multicountry weights corresponds the exact number of units in each level. At the student level, the student weights were created by transforming student final weights (W_FSTUWT) into the Mutlcountry weights that they sum to the number of students in the student level dataset. At the school level, the final school weights (W_SCHGRNRABWT) were transformed into the Multicountry weights so that they sum to the weights equal to the number of schools in the school level dataset. Accordingly, appropriate standard errors for the variables of 58 countries from PISA 2018 dataset can be obtained with each country being represented in proportion to its actual size.

Dependent Variable

In this study, 10 plausible value variables from PISA 2018 were used to measure 15-years old students' mathematics achievement. In PISA 2018 student questionnaire data, students' mathematics achievement that was used is the plausible values (PVs) which is the imputation methodology. PVs can be defined as more than one random variable that is estimated from the multidimensional Item Response Theory (IRT) models. In the large-scale assessments such as PISA and TIMSS, PVs have been used instead of collecting individuals' scores because those assessments have too large a sample size to assess scores of individual students' performance. The PV methodology randomly draws multiple imputed proficiency values from the distribution of proficiency estimates (Jerrim et al., 2019). In PISA 2018, 10 plausible values for each domain (reading, science, and mathematics) were drawn from the proficiency distribution and were used as representative of each domain performance. 10 plausible values in mathematics (PV1MATH to PV10MATH) in the PISA 2018 student questionnaire dataset were used as dependent variables in this study.

There has been a longstanding debate over how to handle plausible values in large scale assessment database. Rutkowski et al. (2010) asserted that two approaches of using plausible values which are incorrect: 1) analyzing only one plausible value and 2) using the mean of all plausible values (usually five to ten plausible values). They argued that those analyzing approaches might misestimate or underestimate standard error estimates. On the other hand, the PISA data analysis manual pointed out that those approaches do not make any make considerable difference in the mean estimates as well as in the standard error estimates when analyzing large sample (OECD, 2009). According to the PISA data analysis manual, using all plausible values is recommended since it guarantees results consistency. Based on the suggestion of the PISA data analysis manual, ten plausible values of students' mathematics achievement will be used as a dependent variable by generating their average in the analysis. The HLM analysis will be conducted through the HLM version 7 software program (Raudenbush et al., 2011), and the HLM program runs each of the numbers of plausible values and generates their average value and the correct standard errors. Accordingly, the 10 HLM parameter estimates from the plausible values will be created and their measurement error will be computed. The descriptive statistics of the dependent variables are shown in Table 3.2.

Table 3. 2. *Dependent Variables Descriptive Statistics*

(N = 455,206*)*

	Minimum	Maximum	Mean	Std. Deviation
Plausible Value 1 in Mathematics	24.74	864.60	456.67	105.28
Plausible Value 2 in Mathematics	25.56	892.73	456.59	105.39
Plausible Value 3 in Mathematics	53.19	910.44	456.57	105.38
Plausible Value 4 in Mathematics	29.97	870.64	456.67	105.52
Plausible Value 5 in Mathematics	8.27	915.10	456.39	105.60
Plausible Value 6 in Mathematics	5.22	870.20	456.48	105.41
Plausible Value 7 in Mathematics	3.21	883.59	456.81	105.59
Plausible Value 8 in Mathematics	0.00	889.80	456.65	105.39
Plausible Value 9 in Mathematics	26.58	899.89	456.45	105.43
Plausible Value 10 in Mathematics	24.92	894.59	456.59	105.57

Independent Variables

This study selected various predictors as student-, school-, and country-level variables based on the literature review. Especially the study was focused on particular variables at each level. A more detailed description of those variables will be addressed in the following. In addition, indices were used as independent variables in this study. Indices refer to the derived variables based on one or more items from PISA 2018 questionnaires. The purpose of constructing indices through items in PISA 2018 was to generate meaningful latent constructs that cannot be observed directly (OECD, n.d.). There are three types of indices in PISA 2018: 1) simple indices, 2) scale indices, and 3) trend scale indices. Simple indices were computed through the mathematical transformation or recoding of one or more items. Scale indices indicate the variables constructed through the scaling of multiple items. The generalized partial credit model (GPCM), one of the item response theory (IRT) models, was used to construct scale indices. The GPCM (Muraki, 1991) is a generalization of the partial credit model (PCM) by adding a parameter for item discrimination to the model. The PCM is an extension of the Rasch model, allowing the use of polytomous items with more than two categories, such as Likert-type items. The equation of GPCM is expressed as follows:

$$\text{P}\ (X_{ji} = k|\theta_j, \beta_i, \alpha_i, d_i) = \frac{exp\ (\sum_{r=0}^{k} D\alpha_i(\theta_j - (\beta_i + d_{ir})))}{\sum_{u=0}^{m_i} exp(\sum_{r=0}^{k} D\alpha_i(\theta_j - (\beta_i + d_{ir})))}$$

where P $(X_{ji} = k)$ is the probability of person *j* to score *k* on item *i* out of the m_i possible scores on the item. θ_j indicates the individual's latent trait, β_i is the difficulty of the item i, α_i is the discrimination parameter for item i, d_{ir} indicates additional step parameters, and D is a scaling factor. After obtaining individual parameters for scales, weighted likelihood estimates (WLE) were used to standardize participant scores so that the mean was zero and the standard deviation was one. Warm (1989) developed a WLE for dichotomous IRT model and less bias estimation can be obtained through WLE compared with maximum likelihood estimation. Lastly, trend scale indices refer to PISA 2018 scale scores that were generated to comparing with those in PISA 2009 using a common calibration linking procedure.

Student-level variables

The primary purpose of the current study is to examine the relationship between students' mathematics achievement and variables at the student, school, and country-level by using multilevel analysis. From the literature reviewed in the previous chapter, various factors have shown that associated with mathematics achievement. Based on the literature reviewed, the following variables were selected as student-level variables: gender, Information, and Communication Technology (ICT) usage, parental education level, parents' emotional support, sense of belonging in school, resilience self-efficacy, mastery goal orientation, fear of failure, occupational aspiration, belief in the belief in the value of school, and growth mindset. All independent variables of the student-level are presented in Table 3.3.

Table 3. 3. *Student Level (Level-1) Variables*

Variable name	**Original item/index name in PISA 2018**	**Short name**	**Description**
Gender	Student Gender	FEM	Female indicator of student’s gender (0=Male, 1=Female)
Parental Education Level	Highest parental education in years of Schooling (PARED)	PARED	Measured by the index of PARED (Range from 3 to 16)
ICT usage	ICT resources (ICTRES)	ICT	Measured by the index of ICTRES (Mean=0, Standard deviation=1)
Parents’ Emotional Support	Parents’ emotional support perceived by student (EMOSUPS)	PARES	Measured by the index of EMOSUPS (Mean=0, Standard deviation=1)

Sense of Belonging in School	Sense of belonging to school (BELONG)	BELN	Measured by the index of BELONG (Mean=0, Standard deviation=1)
Resilience Self-efficacy	Resilience (RESILIENCE)	RSELF	Measured by the index of RESILIENCE (Mean=0, Standard deviation=1)
Mastery goal orientation	Mastery goal orientation (MASTGOAL)	MAG	Measured by the index of MASTGOAL (Mean=0, Standard deviation=1)
Fear of Failure	General fear of failure	FFAIL	Measured by the index of GFOFAIL
Occupational Aspiration	Expected occupational status	OA	Measured the index of BSMJ (Mean=0 Standard deviation=1)
Belief in the value of school	Attitudes towards learning activities (ATTLACT)	VSCH	Measured by the index of ATTLNACT (Mean=0, Standard deviation=1)
Growth Mindset	Growth mindset	GM	Measured by the reversed item ST184 (Mean=0 Standard deviation=1)

The first three variables are demographic characteristics of students: gender (FEM), parental educational level (PARED), and ICT usage (ICT). As the gender variable, the female indicator (1=female, 0=male) was created as a level-1 predictor. Many previous studies have recognized gender differences in mathematics achievement. According to large-scale international assessments, males have higher average mathematics scores than females in most countries. Therefore, researchers and policymakers are interested in understanding girls' lagging math performance. As mentioned in the literature reviewed in the previous chapter, some previous studies have argued that biological differences are associated with achievement gaps in mathematics achievement. Other studies have maintained that cultural norms play an important role in differential gender performance in mathematics. The study explored whether math achievement is different by gender even after controlling for other predictors. In PISA 2018, the question about gender identify is categorized as male and female. The following demographic variable is ICT usage (ICT) which was measured by the index of ICTRES. The ICT usage indicates student's ICT resources availability at home. The ICTRES index was created by standardizing scaling the sum of the responses for questions about possession of ICT resources in household (See Appendix A), each is a 4-point liker scale, with a mean of 0 and a standard deviation of 1. The average of reliabilities (Cronbach's Alpha coefficients) for ICTRES among participated PISA 2018 countries is .50. The last demographic variable of level 1 was parental education level (PARED) which indicates the estimated years of schooling of parents. In this study, the index of PARED was used as the parental education level variable. The index of PARED was recoded from the questions ST005, ST006, ST007, and ST008 (See Appendix A) and ranged from 3 to 18.

Mathematics achievement can be associated with diverse non-cognitive factors. Accordingly, several non-cognitive factors were selected as independent variables of the student level. Eight student-level non-cognitive variables were selected: parents' emotional support (PARES), sense of belonging in school (BELN), resilience self-efficacy (RSELF), mastery goal orientation (MAG), fear of failure (FFAIL), occupational aspiration (OA), the belief in the value of school (VSCH), and growth mindset (GM). Parents' emotional support was measured by the index of EMOSUPS that consists of three items about asking students' perceived emotional support from their parents (ST123) using a four-point Likert scale (See Appendix A). It was transformed to a scale with a mean of 0 and a standard deviation of 1. Sense of belonging in school was measured by the index of BELONG, which was transformed to a standardized scale (mean=0, standard deviation=1) by using six items (ST034) about asking students' sense of belonging in school with four-point Likert scale (See Appendix A). PISA people provided the reliability of each measure constructed from a respective set of items for each country separately. Therefore, in order to provide a measure of reliability of each variable, I will provide the average value across countries. The average Cronbach's Alpha coefficients for the index of BELONG across countries is .75. The variable of resilience self-efficacy was measured by the RESILIENCE index, which consists of five items (ST188) with a four-point Likert scale (See Appendix A). The average Cronbach's Alpha coefficients for the index of RESILIENCE across countries is .78. Self-efficacy and resilience are highly correlated since they share a common concept which is an individual ability to cope with difficulty (Schwarzer & Warner, 2013). The five items (ST188) of PISA 2018 are about measuring students' resilience self-efficacy. As mentioned in Chapter 2, self-efficacy is the individual's belief in completing a specific task or domain. Therefore, self-efficacy always comes with a specific domain. Resilience self-efficacy is self-efficacy for being resilient. The mastery goal orientation variable refers to a student's purpose on focusing on learning and understanding (Ames, 1992) and was measured by the index of MASTGOAL. The index of MASTGOAL was constructed by scaling of three items (ST208) with a five-point Likert scale (See Appendix A). The average Cronbach's Alpha coefficients for the index of MASTGOAL across countries is .86. The fear of failure was measured by the index of GFOFAIL that was constructed by the three items (ST183) with a four-point Likert scale (See Appendix A). The average Cronbach's Alpha coefficients for the index of GFOFAIL across countries is .79. The occupational aspiration variable was created by the index of BSMJ, which stands for the student's expected occupational status. BSMJ was created by rescaling the open-ended question (ST114), "What kind of job do you expect to have when you are about 30 years old?". The responses were coded to four-digit International Standard

Classification of Occupation (ISCO) codes and mapped to the International Socio-Economic Index (ISEI) index (Ganzeboom & Treiman, 2003). A higher score of BSMJ indicates higher levels of a student's occupational aspiration. The BSMJ scores originally ranged from 11.01 to 88.96, with a mean of 66.3. In this study, the scores of BSMJ were standardized as Z-scores by rescaling the score to have a mean of 0 and a standard deviation of 1. Standardization allows us to compare other scores of student-level variables that were already scaled as a mean of 0 and a standard deviation of 1.

The belief in the value of school variable was measured by the index of ATTLANCT, which was transformed to a standardized scale (mean=0, standard deviation=1) by using ST036 items (See Appendix A) about the asking belief in the value of schooling with four-point Likert scales. The average Cronbach’s Alpha coefficients for the index of ATTLANCT across counries is .85. The belief in the value of school variable indicates the belief regarding the belief in the value of school. This variable was measured by the index ATTLNACT, which consists of reversed-coded three items (ST036) (See Appendix A). The last non-cognitive student-level variable was the growth mindset. In PISA 2018, which is the latest PISA assessment, a growth mindset item was included. This variable was measured by item 184Q01HA ("Your intelligence is something about you that you can't change very much"), and the item used a four-point Likert scale including "strongly disagree," "disagree," "agree," or "strongly agree". The growth mindset item was reversed coded so that 4 indicates that a student has a strong growth mindset 1 indicates a student has a strong fixed mindset. Then, the scores of the item were also transformed into Z-scores.

Among student-level variables, ICT usage (ICT), growth mindset (GM), and resilience self-efficacy (RSELF) are the primary focus of the analysis plan because these three variables have engendered lots of controversies. The use of ICT, such as smartphones, laptops, and tablets, has increased substantially since a decade ago, and many policymakers have become interested in the positive effects of ICT on learning outcomes. However, the effects of ICT usage are controversial since the literature on ICT is still under development. Moreover, recent research has focused on the learning process by exploring psychological factors for overcoming the limitations of traditional input-based performance indicators. Growth mindset and resilience self-efficacy have been explored as psychological processes that can explain why some students can overcome difficulty while others languish.

Table 3. 4. *Student-level (Level-1) Descriptive Statistics*

(N = 455,206)

	Minimum	Maximum	Mean	Std. Deviation
Gender (FEM)	0.00	1.00	0.50	0.50
Parental Education Level (PARED)	3.00	18.00	13.52	3.10
ICT usage (ICT)	-4.01	4.01	-0.45	1.16
Parents' Emotional Support (PARES)	-2.45	1.03	-0.05	0.94
Sense of Belonging in School (BELN)	-3.32	3.23	-0.07	0.94
Resilience Self-efficacy (RSELF)	-3.17	2.77	0.07	0.99
Mastery Goal Orientation (MAG)	-2.53	1.85	0.14	1.01
Fear of Failure (FFAIL)	-1.89	1.89	-0.03	0.95
Occupational Aspiration (OA)	-3.12	1.27	-0.01	1.00
Belief in the value of school (VSCH)	-2.54	1.08	0.03	0.98
Growth Mindset (GM)	-1.75	1.54	0.00	1.00

School-level variables

School-level variables as level-2 independent variables include the proportion of female in the school (XFEM), school-mean parental education level (XPARED), school-mean ICT usage (XICT), school-mean parents' emotional support (XPARES), school-mean sense of belonging in school (XBELN), school-mean resilience self-efficacy (XRSELF), school-mean mastery goal orientation (XMAG), school-mean fear of failure (XFFAIL), school-mean occupational aspiration (XOA), school-mean belief in the value of school (XVSCH), school-mean growth mindset (XGM), school locale (RURAL;CITY), Private school (PRIV), student-teacher ratio (STR), the proportion of fully certified teachers (PFCT), class size (CSIZE), extra-curricular activities in school (EXTRA), student behavior hindering learning (SBHL), and teacher behavior hindering learning (TBHL). All school-level variables are presented in Table 3.5.

Table 3. 5. *School Level (Level-2) Variables*

Variable name	**Original item/index name in PISA 2018**	**Short name**	**Description**
Proportion of Female	N/A	XFEM	Proportion of females in school
School-mean Parental education level	N/A	XPARED	Mean of student level parental education level
School-mean ICT Usage	N/A	XICT	Mean of student level ICT usage
School-mean Parents' Emotional Support	N/A	XPARES	Mean of student level perceived parents 'emotional support
School-mean Sense of Belonging in School	N/A	XBELN	Mean of student level sense of belonging in school

School-mean Resilience Self-efficacy	N/A	XRSELF	Mean of student level resilience self-efficacy
School-mean Mastery Goal Orientation	N/A	XMAG	Mean of student level mastery goal orientation
School-mean Fear of Failure	N/A	XFFAIL	Mean of student level fear of failure
School-mean Occupational Aspiration	N/A	XOA	Mean of student level occupational aspiration
School-mean Belief in the value of school	N/A	XVSCH	Mean of student level belief in the value of school
School-mean Growth Mindset	N/A	XGM	Mean of student growth mindset
School Locale	SC001	RURAL	Location of the school (Rural=1, Town =0)
	SC001	CITY	Location of the school (City=1, Town=0)
Type of School	SC013	PRIV	Recoded the index of SCHLTYPE (Public School=0, Private School =1)
Student-Teacher Ratio	Student-teacher ratio (STRATIO)	STR	Measured by the index STRATIO which was obtained by dividing the number of students by the total number of teachers
The Proportion of Fully Certified Teachers	The proportion of fully certified teachers (PROATCE)	PFCT	Measured by the index PROATCE which was computed by dividing number of fully certified teacher by the total number of teachers
Class Size	The average class size	CSIZE	Recoded the index of CLSIZE, the number of students in one classroom
Extra-Curricular Activities in School	Creative extra-curricular activities at school (CREACTIV)	EXTRA	The index of creative extra-curricular activities at school

			(CREACTIV) was computed as the total number of the following activities that occurred at school: 1) Band, orchestra or choir, 2) School play or school musical SC053Q03TA School yearbook, newspaper or magazine, 3) Volunteering or service activities, 4) Book club, 5) Debating club or debating activities, 6) Art club or art activities, 7) Sporting team or sporting activities, 8) Lectures and/or seminars, 9) Collaboration with local libraries, 10) Collaboration with local newspapers, and 11) country specific item
Student Behavior Hindering Learning	Student Behavior Hindering Learning (STUBEHA)	SBHL	The scaling model used six items to reflect student-related factors affecting school climate (STUBEHA: items SC061Q01TA, SC061Q02TA, SC061Q03TA, SC061Q04TA, SC061Q05TA and SC061Q11TA
Teacher Behavior Hindering Learning	Teacher Behavior Hindering Learning (TEACHBEHA)	TBHL	The scaling model five items to reflect teacher-related factors affecting school climate (TEACHBEHA: items SC061Q06TA, SC061Q07TA, SC061Q08TA, SC061Q09TA, and SC061Q10TA)

The school locale variable indicates the type of area where a school is located. In PISA 2018, types of the area were measured by the item SC001Q01TA (See Appendix A) and classified into five categories: 1) a village, 2) a small town, 3) a town, 4) a city, and 5) a large city. In this study, the five categories of the item were minimized into three categories: 1) a rural, 2) a town, and 3) a city. This categorization was defined by the number of people in each area. An area with fewer than 15,000 inhabitants was defined as rural, a place with between 15,000 and 100,000 people was defined as a town, and a place with over 100,000 was defined as a city.

The type of school variable was measured by transforming the index SCHLTYPE. The index of SCHLTYPE has categorized the type of school into three categories: 1) private independent, 2) private government-dependent, 3) public. The variable of the type of school was recoded into two categories: 1) private school (combined private independent and private government-dependent) and 2) public. A private school refers to a school that was managed by a non-government organization and a public school indicates a school was managed by a public education authority, government agency, or governing board appointed by the government or elected by a public franchise (OECD, 2020).

The class size variable (CSIZE) was measured by transforming the index of CLSIZE. The CLSIZE index was driven from the CLSIZE item (See Appendix A). This item was into nine categories: 1) 15 students or fewer, 2) 16-20 students, 3) 21-15 students, 4) 26-30 students, 5) 31-35 students, 6) 36-40 students, 7) 41-45 students, 8) 46-50 students, and 9) more than 50 students. Teachers' related variables at the school level include the student-teacher ratio and the proportion of fully certified teachers. The variable of the student-teacher ratio was measured by the index of STRATIO, which was obtained by dividing the total number of students enrolled by the total number of teachers (See Appendix A). The proportion of fully certified teachers was measured by the PROATCE index, which was based on the item SC018Q02TA (See Appendix A) and computed by dividing the number of fully certified teachers by the total number of teachers. According to PISA 2018, "The number of part-time teachers was weighted by 0.5, and the number of full-time teachers was weighted by 1.0" (Peña-López, 2019, p.219). The values of the item were transformed in the range of 0 to 1. The score 0 indicates 0% of fully certified teachers in the school, and the score 1 indicates 100% of fully certified teachers in the school.

School climate variables were collected from the school questionnaire and are listed as follows: Extra-curricular activities (EXTRA), Student behavior hindering learning (SBHL), and Teacher behavior hindering learning (TBHL). The extra-curricular activities variable (EXTRA) was based on the index of creative extra-curricular activities at school (CREACTIV), which was computed by the school questionnaire (SC053) (See Appendix A). In PISA 2018, school principals were asked to questionnaire that examined what extra-curricular activities at schools offered to 15-year-old students. The student behavior hindering learning (SBHL) variable and teacher behavior hindering learning (TBHL) variable were measured by the index of student behavior hindering learning (STUBEHA) and the index of teacher behavior hindering learning (TEACHBEHA) that were both calculated from the school questionnaire (SC061). The STUBEHA index was measured by the six items asking about the school principal's perception of student behavior that might influence the instruction at school. In the PISA 2018 survey, the items about student behavior hindering learning were: 1) student truancy, 2) student skipping classes, 3) students lacking respect for teachers, 4) student use of alcohol or illegal drugs, 5) students intimidating or bullying other students, and 6) students not being attentive. The average Cronbach's Alpha coefficients for the index of STUBEHA across countries is .81. The TEACHBEHA index was measured by the five items that were collected from school principals by asking about their perception of teacher-related factors that might hinder the learning climate. The five items were: 1) teachers not meeting individual students' needs, 2) teacher absenteeism, 3) staff resisting change, 4) teacher being too strict with students, and 5) teachers not being well prepared for classes. The four response categories, including "Not at all," "Very little," To some extent," and "A lot," were used for scaling those two indices. The average Cronbach's Alpha coefficients for the index of TEACHBEHA across countries is .78.

Among school-level variables, extra-curricular activities in school (EXTRA) are the primary focus of this study since few studies have examined the relationship between extra-curricular activities in school and math achievement. Extra-curricular activities can promote student's creativity (Cunliffe, 2008). Although creativity is crucial to understand the world and to widen people's perspectives, it is not traditionally associated with mathematical proficiency (Švecová et al., 2014). According to Kaufman and Baer (2004), mathematics and science abilities are not related to student perceived general creativity. Therefore, this study focused on the effect of providing extra-curricular activities on mathematics achievement.

Table 3. 6. *School-level (Level-2) Descriptive Statistics*

(J = 13,519*)*

	Minimum	Maximum	Mean	Std. Deviation
Proportion of Female (XFEM)	0.00	1.00	0.49	0.22
School-mean Parental education level (XPARED)	3.00	18.00	13.42	1.79
School-mean ICT Usage (XICT)	-3.96	2.10	-0.51	0.81
Mean Parents' Emotional Support (XPARES)	-2.45	1.03	-0.07	0.39
School-mean Sense of Belonging in School (XBELN)	-3.24	3.22	-0.09	0.38
School-mean Resilience Self-efficacy (XRSELF)	-3.17	2.70	0.04	0.39
School-mean Mastery Goal Orientation (XMAG)	-2.53	1.85	0.13	0.46
School-mean Fear of Failure (XFFAIL)	-1.89	1.89	-0.04	0.36
School-mean Occupational Aspiration (XOA)	-3.09	1.25	-0.07	0.60
School-mean Belief in the value of school (XVSCH)	-2.54	1.08	0.01	0.34
School-mean Growth Mindset (XGM)	-1.75	1.54	-0.00	0.39

School Locale: Rural (RURAL)	0.00	1.00	0.34	0.47
School Locale: City (CITY)	0.00	1.00	0.39	0.49
Type of School (PRIV)	0.00	1.00	0.20	0.40
Student-Teacher Ratio (STR)	0.01	0.90	0.14	0.83
The Proportion of Fully Certified Teachers (PFCT)	0.00	1.00	0.80	0.34
Class Size (CSIZE)	13.00	53.00	27.72	10.45
Extra-Curricular Activities (EXTRA)	0.00	3.00	1.85	1.03
Student Behavior Hindering Learning (SBHL)	-4.35	3.63	0.01	1.26
Teacher Behavior Hindering Learning (TBHL)	-2.09	3.83	0.12	1.16

Country-level variables

At the 3-level, variables from school-level variables were aggregated and new country-level variables were also added. Country-level independent variables included the proportion female in the country (YFEM), country-mean parental education level (YPARED), country-mean ICT usage (YICT), country-mean perceived parents' emotional support (YPARES), country-mean sense of belonging in school (YBELN), country-mean resilience self-efficacy (YRSELF), country-mean mastery goal (YMAG), country-mean fear of failure (YFFAIL), country-mean occupational aspiration (YOA), country-mean belief in the value of school (YVSCH), country-mean growth mindsets (YGM), country-mean school locale: Rural (YRURAL), country-mean school locale: City (YCITY), country-mean type of school (YPRIV), country-mean student-teacher ratio (YSTR), country-mean the proportion of teachers fully certified (YPFCT), country-mean class size (YCSIZE), country-mean extra-curricular activities in school (YEXTRA), country-mean student behavior hindering learning (YBHL), country-mean teacher behavior hindering learning (TBHL), OECD country (OECD), strict university admission system (STRICT), GDP per capita (GDP), Gender Inequality (GG), and GINI Index (GINI).

The strict university admission system (STIRCT) was a dummy variable indicating university admission procedure, with 0=flexible university admission system and 1=strict university admission system. The university admission procedure variable that was measured by the modified Helms's classification of types of university admission procedures. Helms (2009) classified types of university admission procedures into five categories: 1) secondary leaving examinations; 2) entrance examinations; 3) standardized aptitude tests; 4) multiple examinations, and 5) no examinations. (See Appendix B) To minimize the complexity of analysis in this study, this classification was recoded into two categories: 1) strict university admission system and 2) flexible university admission system. The secondary examinations, entrance examinations, and multiple examinations were recoded to the "strict university admission system" because secondary leaving examinations and college entrance examinations both are administered by governments or educational institutions and have strict regulations and limited time for taking examinations. Standardized aptitude tests and no examination were recoded to "flexible university admission system" since standardized aptitude tests do not place limits on taking tests, and countries that have no certain system of examinations generally rely on students' performance or experience during secondary school and have diverse requirements depending on the individual higher institution.

The gross domestic product (GDP) variable was measured by the GDP per capita of 2018 that was published by the World Bank. Exceptionally, the GDP per capita of Taiwan was retrieved from the report from Statista (O'Neill, 2022) since the World Bank does not provide the GDP per capita of Taiwan. The GDP per capita variable was shown in the U.S dollar. Gender inequality was measured by using the index of global gender gap index 2017 (Schwab et al., 2017). The global gender gap index was calculated based on four key areas: health, education, economy, and politics. The highest possible score of the index is 1 and the lowest possible score of the index is 0. A score of 1 indicates the highest level of gender equality and 0 indicates the least amount of gender equality. The GINI index variable was measured by the GINI index coefficient data that was published by the central intelligence agency (CIA). The GINI index refers to a summary measure of income inequality in a country, and the GINI coefficient is ranged from 0, indicating perfect equality to 1, perfect inequality. In this study, the GINI index was reverse-coded so that higher values reflect higher equality.

This study manly focused on strict university admission system (STRICT), country-mean growth mindset (YGM) in the analysis because this study hypothesized that national and cultural characteristics are associated with math achievement and very few studies have examined the association between the university admission system and math achievement by using multilevel analysis. In addition, the country-mean growth mindset is distinct from the growth mindset as a student-level variable since the growth mindset that was aggregated to the country-level refers to the national and cultural characteristics. Therefore, the country-mean growth mindset indicates the country's culture of mindsets about intelligence.

Table 3. 7. *Country Level (Level-1) Variables*

Variable name	**Short name**	**Description**
National Proportion of Female	YFEM	Proportion of females in the country
Country-mean Parental Education Level	YPARED	Mean of the school level parental education level
Country-mean ICT usage	YICT	Mean of school level access to ICT resources usage

Country-mean Parents' Emotional Support	YPARES	Mean of school level perceived parents' emotional support
Country-mean Sense of Belonging in School	YBELN	Mean of school level school engagement
Country-mean Resilience Self-efficacy	YRSELF	Mean of school level resilience self-efficacy
Country-mean Mastery Goal Orientation	YMAG	Mean of school level mastery goal orientation
Country-mean Fear of Failure	YFFAIL	Mean of school level fear of failure
Country-mean Occupational Aspirations	YOA	Mean of school level student occupational aspirations
Country-mean Belief in the value of school	YVSCH	Mean of school level belief in the value of school
Country-mean Growth Mindset	YGM	Mean of school level growth mindset
Country-mean Type of School	YRURAL YCITY	YRURAL: Proportion of rural in the country, YCITY: Proportion of city in the country
Country-mean Type of School (YPRIV)	YPRIV	Mean of school level type of school
Country-mean Student-teacher Ratio	YSTR	Mean of school level student-teacher ratio
Country-mean Fully Certified Teacher	YPFCT	Mean of school level proportion of fully certified teacher
Country-mean Class Size	YCSIZE	Mean of school level class size
Country-mean Extra-Curricular Activities	YEXTRA	Mean of school level extra-curricular activities in school
Country-mean Student Behavior Hindering Learning	YSBHL	Mean of school level student behavior hindering learning

Country-mean Teacher Behavior Hindering Learning	YTBHL	Mean of school level teacher behavior hindering learning
OECD Member	OECD	Member of OECD (OECD=1, No OECD=0)
Strict University Admission System	STRICT	Types of admission procedure in higher education (Strict system=1, Flexible system=0)
Gross Domestic Product	GDP	GDP per capita in 2018 (in U.S dollar) Divided into 10,000
Gender Inequality	GG	Global Gender Gap Report from World Economic Forum (as %)
GINI Index	GINI	Latest report of GINI index measured the degree of inequality in the distribution of family income in a country from Central Intelligence Agency (as %). Revers coded.

Table 3. 8. *Country Level (Level-3) Descriptive Statistics*

(k= 58*)*

	Minimum	Maximum	Mean	Std. Deviation
National Proportion of Female (YFEM)	0.46	0.54	0.50	0.02
Country-mean Parental Education Level (YPARED)	10.89	16.63	13.49	1.18
Country-mean ICT usage (YICT)	-1.93	0.59	-0.51	0.63
Country-mean Parents' Emotional Support (YPARES)	-0.46	0.32	-0.06	0.16
Country-mean Sense of Belonging in School (YBELN)	-0.40	0.46	-0.10	0.19
Country-mean Resilience Self-efficacy (YRSELF)	-0.61	0.60	0.06	0.22
Country-mean Mastery Goal Orientation (YMAG)	-0.34	0.67	0.14	0.28
Country-mean Fear of Failure (YFFAIL)	-0.42	0.67	-0.04	0.23

Country-mean Occupational Aspirations (YOA)	-0.54	0.47	-0.04	0.48
Country-mean Belief in the value of school (YVSCH)	-0.46	0.51	0.01	0.21
Country-mean Growth Mindset (YGM)	-0.64	0.43	-0.01	0.20
Country-mean Type of School: Rural (YRURAL)	0.00	0.71	0.34	0.17
Country-mean Type of School: CITY (YCITY)	0.00	1.00	0.39	0.19
Country-mean Type of School (YPRIV)	0.00	0.90	0.18	0.20
Country-mean Student-teacher Ratio (YSTR)	0.07	0.25	0.13	0.45
Country-mean Fully Certified Teacher (YPFCT)	0.29	0.97	0.79	0.17
Country-mean Class Size (YCSIZE)	16.75	38.93	25.10	5.07
Country-mean Extra-Curricular Activities (YEXTRA)	-1.24	1.09	0.02	0.44
Country-mean Student Behavior Hindering Learning (YSBHL)	-1.53	0.90	-0.07	0.47
Country-mean Teacher Behavior Hindering Learning (YTBHL)	1.02	2.82	1.81	0.45
OECD Member (OECD)	0.00	1.00	0.41	0.50
Strict University Admission System (STRICT)	0.00	1.00	0.90	0.31
GDP per capita (GDP)	0.32	8.64	2.42	2.10
Gender Inequality (GG)	0.58	0.88	0.71	0.05
GINI Index (GINI)	0.46	0.76	0.64	0.07

Methodology

People cannot be regarded as independent units because individuals exist within organizational structures and are influenced by the social organizations to which they belong. Naturally, students are influenced by classrooms managed by teachers within schools, districts, and provinces. Moreover, students are influenced by their cultural context by internalizing cultural values and beliefs. In other words, students within a particular classroom, school, community, and country tend to share experiences of being in the same environment, and this can lead to dependency on the observations. Since educational systems inherently have a hierarchical structure, multilevel models should be used to investigate the relationship between variables at different levels of organizational structure. Multilevel models are developed to analyze from different levels simultaneously by applying statistical models that include various dependencies. The significant advantage of multilevel models is that the models can provide a "more integrated understanding of phenomena that unfold across levels" (Klein & Kozlowski, 2000, p.7).

Hierarchical data structures can comprise two, three, or more levels. For example, students can be nested within higher-level units such as classrooms, and classrooms can be nested within schools; by extension, schools can be nested within districts or countries. Currently, there are many multilevel models for analyzing hierarchical data structure, and Hierarchical Linear Modeling (HLM) will be used in this study. HLM is an extension of single-level multiple linear regressions that explains shared variance in hierarchically structured data (Woltman et al., 2012). A three-level HLM will be used as a primary analytic methodology in this study since the data has a nested structure, with students nested within schools, which in turn nested within countries.

Before the development of HLM, nested data were analyzed using traditional linear models, but these techniques had limits because two significant assumptions were violated: Independence and homoscedasticity. Independence, which means that the residuals are independent, is violated because individuals in the same group tend to have similar characteristics to individuals in different groups. Homoscedasticity is violated by having the clustered nature of the data because within-group and between-group intercept and slope residuals have constant variances, and the variance of the residuals is constant are violated because group components are independent between groups but indeed correlated within groups (Raudenbush & Bryk, 2002). In order to overcome these limitations of using linear regression models, HLM has been applied in social science and education fields with the development of statistical software packages and computer technology.

This study mainly uses HLM to estimate the effects of student, school, and country characteristics on students' mathematical achievement. HLM can determine whether there are significant differences in intercept and slope across each higher-level aggregation. Three-level HLM will be used to analyze the data with a structure consisting of students (level 1) nested within schools (level 2) and nested within countries (level 3). In three-level HLM, level-1 coefficients will be the outcomes in the level-2 model, and the level-2 parameters will be the outcomes in the level-3 model. Accordingly, student outcomes are predicted by level-1, level-2, and level-3 predictors. In this study, models will be developed step by step to demonstrate the three-level HLM. First, a fully unconditional model will be formulated to determine whether the HLM is appropriate for the data. The fully unconditional model will be formulated using mathematic achievement as an outcome variable with no level 1, level 2, or level 3 predictors. If there is significant variation at level 2 and level 3, HLM analysis will be performed.

The fully unconditional model

Raudenbush and Bryk (2002) suggested building fully unconditional models first since it allows to observe evidence of significant between-group variability. The fully unconditional model shows how variation in outcome measures is assigned across three levels including student-, school-, and country-level.

Student-level model

The student-level (level-1) model can be expressed as the following equation

$$Y_{ijk} = \pi_{0jk} + e_{ijk} \tag{1}$$

where

Y_{ijk} is the mathematics achievement of student i in school j and country k;

π_{jk} is the mean mathematics achievement of school j in country k; and

e_{ijk} is a random "student effect," that is, the deviation of student ijk's score from the school-mean. In other words, it represents the random error of student i in school j and country k. These effects are assumed normally distributed with a mean of - and variance of σ^2

i = 1,2, 3...., n_{ijk} students in school j and country k.

j = 1, 2...., J_{jk} schools within country

k= 1...., *K* countries

School-level model

In the school-level (level-2) model, each school math achievement mean, π_{jk}, is viewed as an outcome varying randomly around some country-means:

$$\pi_{0jk} = \beta_{00k} + r_{ijk} \tag{2}$$

where

π_{0jk} is the mean math achievement in country *k*;

β_{00k} is a random "school effect," that is, the deviation of school *jk*'s mean from the country-mean. These effects are assumed normally distributed with a mean of 0 and variance τ_{π} . Within each country *k*, the variability among schools is assumed the same.

Country-level model

In the country-level (level-3) model, country-mean math achievement, β_{00k}, varies randomly around grad mean for all countries:

$$\beta_{00k} = \gamma_{000} + u_{00k} \tag{3}$$

where

γ_{000} is the grand mean mathematics achievement for all countries;

u_{00k} is a random "country effect," that is, the deviation of country *k*'s mean from the grand mean. These effects are assumed normally distributed with a mean of 0 and variance τ_{β}.

The combined model of the three-level fully unconditional model is presented in Equation 4:

$$Y_{ijk} = = \gamma_{000} + u_{00k} + r_{ojk} + \mathrm{e}_{ijk} \tag{4}$$

where γ_{000} represents the grand mean mathematics achievement for all countries; and u_{00k}, r_{ojk}, and e_{ijk} are random variations in the country-mean math achievement. Equation 4 allows us to estimate variability associated with the three levels: student-, school-, and country-level. If there are significant between-group variations, then a three-level HLM analysis will be justified. For justifying the three-level HLM, Intraclass correlation coefficients (ICCs), which represent the proportion of the total variance explained by grouping structure, will be obtained from the fully unconditional model.

The conditional model

After running the unconditional model, conditional models will be run for each variable. Since the primary purpose of this study is to conduct a contextual analysis, finding country-level predictors associated with math achievement was prioritized. Country-level predictors were progressively added to the unconditional model, and school- and student-level variables were applied to models as predictors to examine variations in math achievement. First, country-level predictors will be added to the model and examine the significance of predictors will be. Then, school-level predictors will be included in the model and evaluated, and student-level predictors will be added to find the best fit model.

Summary

In this chapter, the variables to analyze the relationship between student-level, school-level, and country-level variables and ten plausible values for the mathematics domain were described at each level. Also, this chapter covers research methodology, including sampling method, weighting, handling plausible values as dependent variables, and data analysis methodology through HLM.

Chapter 4. Results

This study aims to investigate the association between student mathematics achievement and various variables at the student, school, and country levels. The student-level (level 1) predictors included three demographic variables (gender, Information and Communication Technology (ICT) usage, and parental education level (PARED), and eight non-cognitive variables (parents' emotional support (PARES), sense of belonging in school (BELN), resilience self-efficacy (RSELF), mastery goal orientation (MAG), fear of failure (FFAIL), occupational aspiration (OA), the belief in the value of school (VSCH), and growth mindset (GM)). The school-level (level 2) predictors included compositional variables created by aggregating the student-level variables (the proportion of females in the school (XFEM), the school-mean parental education level (XPARED), school-mean ICT usage (XICT), school-mean parents' emotional support (XPARES), school-mean sense of belonging in school (XBELN), school-mean resilience self-efficacy (XRSELF), school-mean mastery goal orientation (XMAG), school-mean fear of failure (XFFAIL), school-mean occupational aspiration (XOA), school-mean the belief in the value of school (XVSCH), and school-mean growth mindset (XGM)) and school variables (school locale (RURAL;CITY), type of school (PRIV), student-teacher ratio (STR), the proportion of fully certified teacher (PFCT), class size (CSIZE), extra-curricular activities in school (EXTRA), student behavior hindering learning (SBHL), and teacher behavior hindering learning (STBHL)). The country-level (level 3) variables included compositional variables that are obtained by aggregating school-level variables (the proportion female in the country (YFEM), country-mean parental education level (YPARED), country-mean ICT usage (YICT), country-mean parents' emotional support (YPARES), country-mean sense of belonging in school (YBELN), country-mean resilience self-efficacy (YRSELF), country-mean mastery goal (YMAG), country-mean fear of failure (YFFAIL), country-mean occupational aspiration (YOA), country-mean belief in the value of school (Y), country-mean growth mindset, country-mean school locale, country-mean type of school, country-mean student-teacher ratio, country-mean the proportion of teachers fully certified, country-mean class size, country-mean extra-curricular activities in school, country-mean student behavior hindering learning, and country-mean teacher behavior hindering learning) and country variables (OECD country, strict university admission system, GDP per capita, Gender Inequality, and GINI Index)

This chapter starts with bivariate analyses, which involve correlation matrixes between all variables in each level and the dependent variable. Then, hierarchical linear models (HLM) were implemented to explore the relationship between student-level, school-level, and country-level predictors and mathematics achievement. A single cross-sectional data with a three-level structure that is composed of students (level 1) nested within schools (level 2) nested within countries (level 3) will be analyzed. In this study, three-level HLM analyses began with an unconditional model that contained no predictor variables from any level. The unconditional model, also called the one-way ANOVA model, is the first step in a HLM model, and it allows to specify the amount of variation in an outcome variable across the three different levels (Bryk & Raudenbush, 1992). Then, conditional models were built by adding level 3 predictor variables, level 2 predictor variables, and level 1 predictor variables on mathematics achievement.

Descriptive Statistics

This study analyzed three-level units, including student-, school-, and country-level variables. In this chapter, bivariate descriptive statistics, including correlation coefficients, were presented at each level was presented.

Student-Level (Level 1) variables

Based on the literature review, the student-level variables included were the student's gender (FEM), parental education level (PARED), ICT usage (ICT), parents' emotional support (PARES), sense of belonging in school (BELN), resilience self-efficacy (RSELF), mastery goal orientation (MAG), fear of failure (FFAIL), occupational aspiration (OA), belief in the value of school (VSCH), and growth mindsets (GM). Bivariate descriptive statistics were conducted to describe how the dependent variable correlated with level-1 independent variables. Ten plausible values for mathematics performance were used as the dependent variables. Table 4.1 shows the bivariate correlation matrix among the student-level variables with the plausible values for mathematics performance.

Table 4. 1. *Student Level (Level-1) Correlation Matrix*

(N=455,206)

	FEM	PARED	ICT	PARES	BELN	RSELF	MAG	FFAIL	OA	VSCH	GM	PM1~ PM10
FEM	1											
PARED	-.031**	1										
ICT	-.002	.349**	1									
PARES	.080**	.068**	.119**	1								
BELN	.006**	.054**	.099**	.263**	1							
RSELF	-.006**	.030**	.065**	.304**	.306**	1						
MAG	.088**	-.008**	-.026**	.271**	.167**	.390**	1					
FFAIL	.120**	.010**	.030**	-.020**	-.161**	-.095**	.044**	1				
OA	.166**	.095**	.075**	.114**	.057**	.093**	.167**	.036**	1			
VSCH	.088**	-.001	.028**	.199**	.175**	.149**	.281**	.025**	.115**	1		
GM	.016**	.070**	.110**	.045**	.068**	.004**	-.020**	-.122**	.071**	.051**	1	
PM1	-.020**	.222**	.338**	.130**	.116**	.039**	-.024**	.057**	.167**	.028**	.183**	1
PM2	-.018**	.224**	.338**	.132**	.116**	.038**	-.022**	.058**	.168**	.028**	.183**	1
PM3	-.019**	.222**	.337**	.131**	.116**	.039**	-.023**	.061**	.168**	.028**	.183**	1
PM4	-.018**	.223**	.337**	.131**	.114**	.037**	-.023**	.060**	.166**	.029**	.184**	1
PM5	-.019**	.222**	.337**	.131**	.117**	.040**	-.023**	.059**	.166**	.029**	.183**	1
PM6	-.020**	.222**	.337**	.130**	.115**	.037**	-.023**	.059**	.167**	.027**	.183**	1
PM7	-.019**	.223**	.339**	.132**	.117**	.039**	-.022**	.058**	.166**	.027**	.184**	1
PM8	-.019**	.220**	.336**	.131**	.116**	.038**	-.023**	.062**	.167**	.027**	.183**	1
PM9	-.019**	.224**	.336**	.129**	.114**	.037**	-.021**	.060**	.167**	.027**	.181**	1
PM10	-.022**	.224**	.336**	.131**	.116**	.038**	-.024**	.057**	.168**	.028**	.183**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Key:
FEM - gender
PARED – parental education level
ICT – availability ICT resources in home
PARES – perceived parents' emotional support
BELN – sense of belonging in school
RSELF – resilience self-efficacy
MAG – mastery goal orientation
FFAIL- fear of failure
OA – occupational aspiration
VSCH – belief in the value of school
GM – growth mindset
PM1 ~ PM10 – plausible values for mathematics performance

As shown in Table 4.1, all the student-level variables had significant correlations at the 0.01 level with the dependent variables, plausible values for mathematics performance (PM1 to PM10). Among the level-1 predictors, ICT usage (ICT) had the strongest positive correlation with the dependent variables (r=0.34, with PM1). This indicates that students who have more

ICT resources at home are more likely to show higher mathematic achievement. The second strongest predictor of math achievement was parental education level (PARED), which has a positive correlation of around 0.22 (with PM1). The growth mindset (GM) (r=0.183, with PM1) and resilience self-efficacy (RSELF) (r=0.39, with PM1), the significant predictors of interest at the student-level, both had a positive relationship with mathematics achievement. The strongest negative correlation variable was the mastery goal orientation (MAG) (r=-0.024, with PM1). This is an interesting result because mastery goal orientation is generally considered an important predictor of students' academic success (Hsieh et al., 2007; Stec, 2015). This result indicated that students with higher mastery goal orientation show lower mathematics achievement.

School-Level (Level 2) variables

School-level variables included the proportion of females in the school (XFEM), school-mean parental education level (XPARED), school-mean ICT usage (XICT), school-mean perceived parents' emotional support (XPARES), school-mean sense of belonging in school (XBELN), school-mean resilience self-efficacy (XRSELF), school-mean mastery goal orientation (XMAG), school-mean fear of failure (XFFAIL), school-mean occupational aspiration (XOA), school-mean belief in the value of school (XVSCH), school-mean growth mindsets (XGM), two dummy groups in terms of school locale that town (TOWN=0) was the reference group and rural (RURAL) and city (CITY), a dummy variable (PRIV) indicating school type with 0=public and 1= private, student-teacher ratio (STR), the proportion of fully certified teacher (PFCT), class size (CSIZE), extra-curricular activities at school (EXTRA), student behavior hindering learning (SBHL), and teacher behavior hindering learning (TBHL). The school-level variables included compositional variables that were generated by aggregating student-level variables. Table 4.2 shows the bivariate correlation matrix among the school-level variables with the school-mean plausible values for mathematics (XPM1 to XPM2).

Table 4. 2. *School Level (Level-2) Correlation Matrix*

(*J* = 13,519)

	XFEM	XPARED	XICT	XPARES	XBELN	XRSELF	XMAG	XFFAIL	XOA	XVSCH	XGM	STR	PFCT	CSIZE	EXTRA	SBHL	TBHL	RURAL	CITY	PRIV	XPM1~ XPM10
XFEM	1																				
XPARED	.015	1																			
XICT	.035**	.623**	1																		
XPARES	.184**	.176**	.223**	1																	
XBELN	.103**	.170**	.186**	.424**	1																
XRSELF	.060**	.007	.011	.419**	.375**	1															
XMAG	.122**	-.113**	-.254**	.302**	.117**	.480**	1														
XFFAIL	.113**	.059**	.145**	.035**	-.159**	-.123**	-.040**	1													
XOA	0	-.089**	-.101**	.038**	-.004**	.121**	.178**	-.008**	1												
XVSCH	.147**	-.028**	.012	.359**	.314**	.263**	.373**	.032**	.269**	1											
XGM	.067**	.258**	.378**	.137**	.163**	-.050**	-.142**	-.015	.118**	.078**	1										
STR	.043**	-.134**	-.232**	-.005	-.080**	.046**	.154**	.061**	.152**	.116**	-.017*	1									
PFT	-0.014	.028**	.075**	-.024**	.008	-.134**	-.159**	.038**	-.085**	-.045**	.068**	-.065**	1								
CSIZE	.086**	-.101**	-.146**	.031**	-.033**	.084**	.119**	.111**	.223**	.110**	-.043**	.366**	-0.001	1							
EXTRA	.097**	.107**	.155**	.154**	-.016	.047**	.042**	.153**	.122**	.049**	.103**	.021*	.058**	.097**	1						
SBHL	-.066**	-.150**	-.112**	-.139**	-.129**	-.069**	-.065**	-.077**	-.165**	-.081**	-.025**	.064**	.052**	.040**	-.103**	1					
TBHL	-.012	-.050**	-.026**	-.034**	-.060**	-.032**	0.005	-.016	.008	.017	.037**	.041**	0.012	.075**	-.039**	.640**	1				
XRURAL	-.030**	-.243**	-.255**	-.069**	-.042**	-.035**	.074**	-.137**	-.165**	-.037**	-.184**	-.146**	-0.01	-.237**	-.120**	-0.01	-.044**	1			
XCITY	.021*	.215**	.210**	.075**	.031**	.048**	0.01	.142**	.197**	.033**	.161**	.110**	-.021*	.204**	.124**	-.029**	.042**	-.577**	1		
XPRIV	.010	.242**	.257**	.150**	.124**	.089**	.022*	.128**	.174**	.127**	.087**	.056**	-.172**	.019*	.064**	-.212**	-.084**	-.189**	.209**	1	
XPM1	.085**	.464**	.609**	.262**	.252**	-.046**	-.215**	.205**	.182**	.002	.388**	-.179**	.160**	-.036**	.242**	-.202**	-.046**	-.229**	.205**	.157**	1
XPM2	.083**	.464**	.606**	.263**	.255**	-.044**	-.209**	.203**	.185**	.003	.390**	-.180**	.161**	-.037**	.240**	-.202**	-.044**	-.229**	.205**	.160**	1
XPM3	.082**	.462**	.608**	.263**	.252**	-.043**	-.214**	.206**	.185**	.003	.386**	-.177**	.162**	-.036**	.241**	-.203**	-.048**	-.233**	.206**	.160**	1
XPM4	.082**	.460**	.606**	.262**	.251**	-.048**	-.215**	.208**	.178**	.004	.388**	-.178**	.161**	-.035**	.241**	-.203**	-.045**	-.231**	.206**	.160**	1
XPM5	.080**	.461**	.608**	.264**	.255**	-.041**	-.210**	.204**	.181**	.003	.385**	-.180**	.160**	-.038**	.240**	-.204**	-.047**	-.229**	.206**	.162**	1
XPM6	.084**	.460**	.606**	.261**	.253**	-.046**	-.213**	.205**	.183**	.003	.388**	-.177**	.163**	-.035**	.241**	-.203**	-.046**	-.233**	.207**	.158**	1
XPM7	.084**	.459**	.605**	.262**	.252**	-.045**	-.215**	.206**	.179**	.002	.390**	-.179**	.163**	-.038**	.240**	-.201**	-.046**	-.230**	.205**	.160**	1
XPM8	.083**	.459**	.605**	.262**	.255**	-.043**	-.213**	.205**	.184**	.002	.385**	-.178**	.161**	-.035**	.241**	-.204**	-.048**	-.230**	.207**	.159**	1
XPM9	.082**	.462**	.605**	.261**	.253**	-.045**	-.212**	.205**	.183**	.001	.388**	-.178**	.164**	-.035**	.242**	-.202**	-.046**	-.229**	.206**	.156**	1
XPM10	.079**	.462**	.605**	.263**	.255**	-.044**	-.216**	.200**	.181**	.004	.387**	-.179**	.162**	-.034**	.241**	-.201**	-.044**	-.230**	.206**	.158**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Key:
XFEM – the proportion of female in school
XPARED – school-mean parental education level
XICT – school-mean availability ICT resources in home
XPARES – school-mean perceived parents' emotional support
XBELN- school-mean sense of belonging in school
XRSLEF – school-mean resilience self-efficacy
XMAG – school-mean mastery goal orientation
XFFAIL – school-mean fear of failure
XOA – school-mean occupational aspiration
XVSCH – school-mean belief in the value of school
XGM- school-mean growth mindset
STR – student-teacher ratio in school
PFCT – the proportion of fully certified teacher in school
CSIZE – class size
EXTRA – extra-curricular activities in school
SBHL – student behavior hindering learning
TBHL – teacher behavior hindering learning
RURAL – school locale: rural
CITY – school locale: city
PRIV – type of school: private
XPM1 ~ XPM10 – school-mean plausible values for mathematics performance

Table 4.2 shows that all the school-level variables had significant correlations at the 0.01 level with the school-mean plausible values for mathematics performance (XPM1 to XPM10), except one variable. The one variable was the school-mean belief in the value of school (XVSCH) had a very low relationship with school-mean mathematics performance (r=0.02, with XPM1) and was not statistically significant at the 0.01 level. Among the compositional variables that were created by aggregating the student-level variables, the school-mean ICT resources (XICT) had the strongest positive correlation with the school-mean plausible values for mathematics performance (r=0.609, with XPM1). This indicates that as schools have more students with richer ICT resources, the school-mean mathematics performance increases. The second strongest positive correlation variable was the school-mean parental education level (XPARED) (r=0.464, with XPM1). This showed that as schools have a higher proportion of high parental education level, the school-mean of mathematics achievement increased. The student-teacher ratio (STR), which is a specific variable of research interest, had a negative association with the school-mean math achievement (r=-0.179, with XPM1). In addition, the extra-curricular activities (EXTRA), which is another main predictor of interest in the study, had the strongest positive correlation with the dependent variables (r=0.242, with XPM1). This indicated schools that offer more extra-curricular activities show higher school-mean mathematics achievement.

From compositional variables, the school-mean mastery goal orientation (XMAG) had the strongest negative association with the dependent variables. Without the compositional variables, the variable that had the strongest negative relationship with the dependent variables was the dummy variable indicating schools located in rural areas (RURAL) (-0.229). This can be interpreted that schools in rural areas had less school-mean mathematics achievement than their city counterpart. The other variable that had the second strongest negative correlation was the student behavior hindering learning (SBHL) (-0.202). This result indicated that as students' hindering behaviors in schools increase, the school-mean of mathematics performance decrease.

Country-Level (Level 3) variables

Country-level variables included the variables generated by aggregating level-2 variables and new added country-level variables as follow: the proportion female in the country (YFEM), country-mean perceived parents' emotional support (YPARED), country-mean availability ICT resources (YICT), country-mean perceived parents' emotional support (YPARES), country-mean sense of belonging in school (YBELN), country-mean resilience self-efficacy (YRSELF), country-mean mastery goal (YMAG), country-mean fear of failure (YFFAIL), country-mean occupational aspiration (YOA), country-mean belief in the value of school (YVSCH), country-mean growth mindsets (YGM), country-mean school locale: Rural (YRURAL), country-mean school locale: City (YCITY), country-mean type of school (YPRIV), country-mean student-teacher ratio (YSTR), country-mean the proportion of teachers fully certified (YPFCT), country-mean class size (YCSIZE), country-mean extra-curricular activities in school (YEXTRA), country-mean student behavior hindering learning (YBHL), country-mean teacher behavior hindering learning (TBHL), OECD country (OECD), university admission procedure (STRICT), GDP per capita (GDP), Gender Inequality (GG), and GINI Index (GINI). Table 4.3 shows the bivariate correlation matrix among the country-level variables with the country-mean plausible values for mathematics (YPM1 to YPM10).

Table 4. 3. *Country Level (Level-3) Correlation Matrix*

(*K* = 58)

	YFEM	YPARED	YICT	YPARES	YBELN	YRSELF	YMAG	YFFAIL	YOA	YVSCH	YGM	YRURAL	YCITY	YSTR	YPRIV	YPFCT	YCSIZE	YEXTRA	YSBHL	YTBHL	OECD	STRICT	GDP	GG	GINI	YPV1~ YPV10
YFEM	1																									
YPARED	-.304*	1																								
YICT	-.379**	.658**	1																							
YPARES	-0.09	0.18	.301*	1																						
YBELN	-.280*	.268*	0.21	.577**	1																					
YRSELF	0.02	-.261*	-.281*	.416**	0.24	1																				
YMAG	0.22	-.378**	-.529**	0.22	-0.10	.603**	1																			
YFFAIL	0.22	-0.08	0.15	-0.05	-.307*	-.377**	-0.17	1																		
YOA	0.20	-.354**	-.286*	0.10	-0.20	.492**	.635**	0.01	1																	
YVSCH	0.07	-0.21	-0.09	.521**	.321*	.317*	.458**	0.02	.423**	1																
YGM	-0.25	.370**	.579**	0.23	0.19	-0.23	-.397**	0.11	-0.14	0	1															
YRURAL	-0.06	0.1	-0.19	0.03	-0.04	0.16	.272*	-.399**	0.01	0	-0.19	1														
YCITY	0.07	-0.2	-0.01	-0.09	-0.08	-0.09	0.05	.466**	.268*	0.06	0.09	-.793**	1													
YSTR	.324*	-.466**	-.479**	-0.14	-0.24	0.18	.417**	0.04	.335*	0.25	-0.22	-0.11	0.09	1												
YPRIV	0.08	-0.09	0.16	0.11	-0.01	-0.08	0.00	.338**	0.19	0.22	-0.10	-.303*	.291*	0.13	1											
YPFCT	-0.07	.264*	.341**	-0.08	0.07	-.428**	-.469**	0.17	-.402**	-0.13	0.16	-0.11	-0.02	-.288*	-0.17	1										
YCSIZE	0.24	-.508**	-.353**	-0.16	-0.18	0.05	0.17	.336**	.345**	0.19	-.265*	-.583**	.604**	.364**	0.25	-0.07	1									
YEXTRA	-0.06	-0.08	0.06	-0.12	-0.19	-0.22	-0.07	0.09	0.07	0.13	0.19	-0.24	0.2	0.18	.301*	-0.05	0.19	1								
YSBHL	0.01	-0.02	-0.06	-0.26	-0.21	-0.09	-0.20	-0.13	-0.19	-0.16	0.15	-0.07	-0.1	0.25	-0.21	0.14	0.02	.647**	1							
YTBHL	-0.12	0.06	.304*	.302*	-0.03	-0.03	-0.05	.399**	-0.11	0.10	0.14	-0.18	0.1	-0.08	0.22	0.18	0.01	0.08	-0.09	1						
OECD	-0.10	0.24	.483**	0.23	.308*	-0.21	-.446**	0.1	-.286*	-0.07	.523**	-0.16	-0.1	-0.03	0.03	0.10	-0.22	-0.01	0.02	0.11	1					
UAP	0.16	-0.08	-0.17	-0.14	-0.12	-0.17	-0.06	0.2	-0.05	-0.20	-0.09	0.06	0.0	0.19	0.00	0.04	-0.05	-0.10	-0.01	0.03	0.06	1				
GDP	-0.25	.472**	.776**	.389**	.269*	-0.24	-.284*	.272*	-0.15	0.17	.470**	-0.23	0.1	-0.22	.269*	0.23	-0.20	0.12	-0.15	.333*	.483**	-0.14	1			
GG	-0.03	.376**	.299*	.330*	0.21	-0.08	-.293*	0.00	-.376**	-0.12	.335*	0.14	-.353**	-0.09	-0.15	0.19	-.411**	-0.01	0.11	0.12	.333*	0.12	.311*	1		
GINI	.262*	-.544**	-.456**	-0.12	-0.26	0.22	.432**	0.20	.607**	.339**	-0.19	-.301*	.457**	.480**	.275*	-0.18	.560**	0.18	-0.03	0.00	-.331*	-0.06	-0.13	-.278*	1	
YPM1	-.360**	.381**	.703**	0.095	0.205	-.513**	-.661**	.362**	-.466**	-.270*	.527**	-.308*	0.189	-.467**	0.1	.434**	-0.177	0.084	-0.05	.430**	.476**	0.142	.574**	.281*	.391**	1
YPM2	-.360**	.381**	.701**	0.097	0.206	-.512**	-.657**	.361**	-.465**	-.270*	.528**	-.304*	0.188	-.467**	0.097	.433**	-0.181	0.082	-0.05	.429**	.476**	0.147	.573**	.286*	.392**	1
YPM3	-.361**	.379**	.702**	0.097	0.205	-.508**	-.657**	.362**	-.463**	-.271*	.527**	-.305*	0.189	-.466**	0.096	.435**	-0.18	0.082	-0.048	.432**	.475**	0.142	.573**	.280*	.390**	1
YPM4	-.359**	.378**	.700**	0.096	0.203	-.509**	-.657**	.366**	-.466**	-.271*	.526**	-.307*	0.189	-.463**	0.096	.433**	-0.177	0.082	-0.048	.434**	.474**	0.147	.573**	.285*	.390**	1
YPM5	-.357**	.378**	.701**	0.097	0.204	-.510**	-.658**	.363**	-.465**	-.271*	.526**	-.307*	0.19	-.466**	0.099	.435**	-0.175	0.085	-0.047	.431**	.477**	0.142	.573**	.280*	.391**	1
YPM6	-.355**	.375**	.698**	0.097	0.204	-.511**	-.656**	.366**	-.462**	-.269*	.525**	-.306*	0.19	-.465**	0.099	.433**	-0.177	0.081	-0.052	.431**	.473**	0.148	.572**	.281*	.387**	1
YPM7	-.357**	.378**	.700**	0.099	0.205	-.512**	-.659**	.365**	-.467**	-.271*	.527**	-.304*	0.187	-.465**	0.096	.434**	-0.179	0.08	-0.05	.433**	.474**	0.146	.574**	.286*	.391**	1
YPM8	-.359**	.376**	.698**	0.096	0.206	-.510**	-.657**	.364**	-.465**	-.270*	.524**	-.307*	0.191	-.465**	0.094	.433**	-0.175	0.079	-0.052	.430**	.475**	0.146	.573**	.281*	.390**	1
YPM9	-.361**	.377**	.700**	0.096	0.204	-.511**	-.658**	.362**	-.465**	-.272*	.525**	-.306*	0.191	-.468**	0.098	.436**	-0.177	0.081	-0.05	.433**	.474**	0.141	.572**	.278*	.388**	1
YPM10	-.357**	.380**	.699**	0.097	0.209	-.513**	-.662**	.360**	-.468**	-.271*	.525**	-.307*	0.188	-.470**	0.094	.436**	-0.176	0.083	-0.048	.427**	.476**	0.144	.574**	.283*	.392**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Key:
YFEM – the proportion of female in country
YPARED – country-mean parental education level
YICT – country-mean availability ICT resources in home
YPARES – country-mean perceived parents’ emotional support
YBELN- country-mean sense of belonging in school
YRSLEF – country-mean resilience self-efficacy
YMAG – country-mean mastery goal orientation
YFFAIL – country-mean fear of failure
YOA – country-mean occupational aspiration
YVSCH – country-mean belief in the value of school
YGM- country-mean growth mindset
YRURAL – country-mean school locale: rural
YCITY – country-mean school locale: city
YPRIV – country-mean type of school: private
YSTR – country-mean student-teacher ratio in school
YPFCT – the proportion of fully certified teacher in school
YCSIZE – country-mean class size
YEXTRA – country-mean extra-curricular activities in school
YSBHL – country-mean student behavior hindering learning
YTBHL – country-mean teacher behavior hindering learning
OECD – OECD country
UAP – university admission procedure
GDP – GDP per capita
GG – gender inequality
GINI – GINI index
YPM1 ~ YPM10 – country-mean plausible values for mathematics performance

The results from Table 4.3 showed that 17 variables have a statistically significant correlation with the country-mean plausible values for country-mean mathematics performance at the 0.01 level and 0.05 level. These variables included: the proportion of females in the country (YFEM), country-mean parental education level (YPARED), country-mean ICT usage (YICT), country-mean resilience self-efficacy (YSELF), country-mean mastery goal orientation (YMAG), country-mean fear of failure (YFFAIL), country-mean occupational aspiration (YOA), country-mean belief in the value of school (YVSCH), country-mean growth mindsets (YGM), country-mean school locale: rural (YRURAL), country-mean student-teacher ratio (YSTR), country-mean the proportion of teachers fully certified (YPFCT), country-mean teacher behavior hindering learning (YTBHL), OECD country (OECD), GDP per capita (GDP), gender inequality (GG), and GINI Index (GINI). The variables that have no statistically significant correlation with the country-mean plausible values for mathematics performance included: country-mean perceived parents' emotional support (YPARES), country-mean sense of belonging in school (YBELN), country-mean school locale: city (YCITY), country-mean type of school: private (YPRIV), country-mean class size (YCSIZE), country-mean extra-curricular activities in school (YCREA), country-mean student behavior hindering learning (YSBHL), and the variable indicating strict university admission system (STRICT).

The strict university admission system (STRICT) and country-mean growth mindsets (YGM) were the main predictors of interest in this study, and it found that both had a positive association with the country-mean plausible values for mathematics performance (YPM1 to YPM10). The STRICT variable had a positive correlation with the dependent variable around 0.142 (with YPM1), which indicates that countries with strict university admission systems have a higher score than countries with flexible university admission systems in country-mean math achievement. The YGM variable also had a positive correlation with the dependent variable around 0.527 (with YPM), which indicates that countries have a social atmosphere that people believe intelligence can be developed through learning and effort have higher scores in math achievement than countries that have a social atmosphere that people believe individual's effort cannot develop intelligence.

From compositional variables that were created by aggregating school-level variables, country-mean ICT usage had the strongest positive correlation with the country-mean plausible values for mathematics performance (YPM1 to YPM10) which was 0.703 (with YPM1). This variable showed that it has the strongest positive statistically significant correlation even after aggregating to the school and country level. The second strongest predictor of math achievement was parental education level (PARED), which has a positive correlation of around 0.22 (with PM1). This variable showed that it has the strongest positive statistically significant correlation even after aggregating to the school and country level. The variable that had the second strongest positive correlation with YPM1 among compositional variables was the country-mean growth mindsets (YGM) (r=0.527). Besides compositional variables, the GDP per capita (GDP) had the strongest positive correlation with YPM1 among country-level variables (r=0.574). This result showed that countries with larger GDPs have higher country-mean mathematics performances. In addition, the variable indicating whether the country is an OECD member (OECD) had the second strongest positive correlation with YPM1 (r=0.476). This indicated that countries that are OECD members show higher country-mean mathematics performances.

The country-mean mastery goal orientation (YMAG) had the strongest negative correlation with the YPM1 among compositional variables (r=-0.661). Interestingly, the country-mean resilience self-efficacy (YRSELF) had the second strongest negative correlation with the

YPM1, while student-level resilience self-efficacy (RSELF) had a positive correlation with students' mathematics achievement (r=0.37, with PM1). Among country-level variables other than compositional variables, there were no variables that had a negative correlation with the country-mean mathematics performances.

Hierarchical Linear Models (HLM)

Model 1: Fully unconditional model

The HLM analysis of this study began with a fully unconditional model, which is also called a null model. Since this model included no predictor variables at any level, it does not explain any variance of the outcome variables. However, this model can confirm whether conducting hierarchical linear modeling (HLM) is the correct choice for our analysis. In response to the first research question in this study, the fully unconditional model was estimated. The fully unconditional model also called the one-way ANOVA model, provides information about outcome variability at each of the three levels (Raudenbush &Bryk, 2002). The HLM equations of the fully unconditional models are represented as follows:

Equation 1. *Equations for Unconditional Model (Model 1)*

Student-Level (Level 1) Model:

$$\mathrm{PVMATH}_{\mathrm{ijk}} = \pi_{0\mathrm{jk}} + e_{\mathrm{ijk.}}$$

School-Level (Level 2) Model:

$$\pi_{0\mathrm{jk}} = \beta_{00\mathrm{k}} + \gamma_{0\mathrm{jk.}}$$

Country-Level (Level 3) Model:

$$\beta_{00\mathrm{k}} = \gamma_{000} + u_{00\mathrm{k.}}$$

In the unconditional model, $\mathrm{PVMATH}_{\mathrm{ijk}}$ represents the mathematics achievement of student i in school j and country k. For PVMATH outcome variable, the average values of 10 plausible values were used. The HLM7 software conducts a separate HLM analysis for each plausible value. Accordingly, the HLM produces plausible values' average value and the standard errors. It seems to be one estimate, but ten HLM estimates by using the ten plausible values were generated with their average and measurement error. $\pi_{0\mathrm{jk}}$ represents the mean math achievement of school j within country k and e_{ijk} indicates the random error associated with student i in school j and country k with the assumption that the random error follows normal distribution with a mean of 0 and a variance of σ^2, which can be represented $e_{\mathrm{ijk}} \sim N(0, \sigma^2)$. At the school-level, the intercept $\beta_{00\mathrm{k}}$ represents the mean mathematics achievement in country k and $\gamma_{0\mathrm{jk}}$ indicates the random error is associated with school j in country k with the assumption that the random error follows normal distribution with a mean of 0 and a variance of τ_π, which can be denoted $\gamma_{0\mathrm{jk}} \sim N(0, \tau_\pi)$. At the country-level, γ_{000} represents the average of mathematics achievement for all countries and $u_{00\mathrm{k}}$ indicates the level-3 random effect follows normal distribution with a mean of 0 and a variance of τ_β, which can be represented $\beta_{00\mathrm{k}} \sim N(0, \tau_\beta)$.

All results for the model can be found in the Table 4.4. As shown in the table, γ_{000} which represents the average mathematics achievement score for 58 countries is 439.16. The estimated variance components from the model were σ^2= 4506.93, τ_π= 2916.65, and τ_β= 3382.67 at the student, school, and country level. Based on the variance components found from this model, the amount of variance explained by each level can be calculated as follow:

The proportion of variance between students:

$$\sigma^2 / (\sigma^2 + \tau_\pi + \tau_\beta)$$

The proportion of variance between schools:

$$\tau_\pi \,/\, (\sigma^2 + \tau_\pi + \tau_\beta)$$

The proportion of variance between counties:

$$\tau_\beta / (\sigma^2 + \tau_\pi + \tau_\beta)$$

According to the equations above, this model found that 41.71% of the variation in mathematics achievement was due to difference among students, and 26.99% of the total variance in math achievement was attributable to differences among schools. Lastly, 31.30% of the variance in math achievement was accounted for by difference among countries. Since the school variance component and country variance component are both significant and the variability in math achievement at the school- and country-level were large, conducting a HLM is necessary to be processed. It is interesting to note that the proportion of variance between countries was larger than of variance between schools since it indicates country-level factors were important in terms of predicting mathematics achievement. Accordingly, conducting multilevel modeling with country-level variables is needed. The next step in model building process was to add predictor variables at level 3 since the main purpose of this study is conducting a cross-national study. The fixed effect tables are less important in a fully unconditional model but are presented in Table 4.4. As shown in the table, the mean math achievement score (the intercept at level 1) is estimated to be 417.49.

Model 2-A: Country-level main predictors without compositional variables model

As checked in the null model, 31.30% of the variance in math achievement was accounted for by country-level differences. Therefore, the country-level model was elaborated in response to the second research question. The model 2-A, 2-B, and 2-C were fitted after completing the fully unconditional model. Firstly, in model 2-A, the level-3 predictors without predictor variables aggregated from student- and school-level were added. Then, compositional variables were added to the next model to see whether there was any change in statistical associations after controlling for those predictors. The country-level predictors added in this model were: OECD country (OECD), strict university admission system (STRICT), GDP per capita (GDP), gender inequality (GG), and GINI index (GINI). Equations for the model are described as follows:

Equation 2. *Equations for Country-level Main Predictors without Compositional Variables Model (Model2-A)*

Student-Level (Level 1) Model:

$PVMATH_{\mathrm{ijk}} = \pi_{0\mathrm{jk}} + e_{\mathrm{ijk}}.$

School-Level (Level 2) Model:

$\pi_{0\mathrm{jk}} = \beta_{00\mathrm{k}} + \gamma_{0\mathrm{jk}}.$

Country-Level (Level 3) Model:

$\beta_{00\mathrm{k}} = \gamma_{000} + \gamma_{001}(OECD_k) + \gamma_{002}(STRICT_k) + \gamma_{003}(GDP_k) + \gamma_{004}(GG_k) + \gamma_{005}(GINI_k) + u_{00\mathrm{k}}.$

Raudenbush and Bryk (2002) refer to this model as the means-as-outcomes. The motivation of the means-as-outcomes model is the hypothesis that there are country differences in mathematics achievement. The means-as-outcomes model can also be called the random intercept model or intercepts-as-outcomes model. This model can examine whether the country-level variables predict the country's mean mathematics achievement. As shown in the equations above, the only difference between the fully unconditional model (Model-1) and the means-as-outcomes model (Model-2) is the addition of the level-3 predictors that were multiplied by the slopes(γ_{001}, γ_{002}, γ_{003}, γ_{004}, and γ_{005}). In the equations of this model, level 1 and level 2 predictors are not included but level 3 variables are added to the model to aggregate the effect at the country-level. In this model, all the level-3 predictors were grand mean centered to make the interpret as more interpretable by adjusting mean for group *k*, which is country-level group. Therefore, the intercept can be interpreted as the expected value of the outcome variable when the values of all predictors are equal to their mean. Country-level explanatory variables, $OECD_k$, $STRICT_k$, GDP_k, GG_k, and $GINI_k$. were used to explain $\beta_{00\mathrm{k}}$, which is mean achievement for country *k*. As sown in the Table 4.4, the model found that three variables were statistically significant associated with country-mean math achievement (YPM1 to YPM10).

The variable STRICT which is a dichotomous variable that identifies the country has strict university admission systems (1) or flexible university admission system (0) was found to have statistically significant positive association with the country-mean mathematics achievement (YPM1 to YPM10), the dependent variable (γ_{002}=47.63, p$\leq$ 0.05). This coefficient suggested that countries that have strict university admission systems show 47.63 points higher than countries that have flexible university admission systems. In addition, The GDP per capita (GDP) (γ_{003}=25.00, p$\leq$ 0.001) and GINI Index (GINI) (γ_{005}=276.28, p$\leq$ 0.01) also had a positive relationship with the dependent variable.

The Table 4.5 presented the amount of variance accounted for at each level and the pseudo- R^2 for each level in all models. pseudo- R^2 indicates how much proportion of variability of mean math achievement across countries was explained by level 3 predictors. There are no level 1 predictors in the means-as-outcomes model as with the fully unconditional model. However, the means-as-outcomes model has predictors at level 3. Therefore, the variability of the level 3 residuals (τ_{β}) must decrease when a meaningful level 3 predictors have been added in the model. Since the level-3 variance component (τ_{β}) decreased from 3382.67 to 1602.27, it can be interpreted that the meaningful predictors were added in this model.

As can be seen in the table, the level-3 pseudo- R^2 (${\mathrm{R}^2}_{L-3}$) for this model was 52.63%. This means that 52.63% of the country level variance of country-mean math achievement scores was explained by OECD country, types of university admissions, GDP per capita, gender inequality, and GINI index. There was no change in level-1 and level-2 intercept variance since only level-3 variables were used to explain $\beta_{00\mathrm{k}}$ (mean math achievement for country *k* in the population). In other words, 52.63% of the true between-country variance in math achievement is accounted for by those five predictors. After removing effects of the five predictors, the correlation between pairs of scores in the same country, which had been 31.30% in the null model, is reduced by 17.75% in this model.

Model 2-B: Country-level main predictors with compositional variables created by school-level variables model

In the model 2-B, five country-level variables were applied in the model 2-A and nine compositional variables that were created by aggregating school-level variables were added. Nine compositional variables obtained by aggregating school-level variables were: country-mean school locale: rural (YRURAL), country-mean school locale: city (YCITY), country-mean types of schools: private school (YPRIV), country-mean student-teacher ratio (YSTR), country-mean proportion of fully certified teachers (YPFCT), country-mean class size (YCSIZE), country-mean extra-curricular activities in school (YCREA), country-mean teacher behavior hindering learning (YTBHL), and country-mean student behavior hindering learning (YSBHL). These compositional variables obtained by aggregating school-level variables have different meanings than school-level variables. These variables can be interpretated as a country's characteristics and culture. For example, the school-level variable (PRIV) identifying the school is a private school (1) or public school (0) is distinct from the meaning of the percentage of private school in a country (YPRIV). This is called 'shift of meaning' (Snijders & Bosker, 2011). All country-level predictors in this model were grand mean centered and the equations for the model are described as follow:

Equation 3. *Equations for Country-level Main Predictors with Compositional Variables Created by School-level Variables Model (Model2-B)*

Student-Level (Level 1) Model:

$$\text{PVMATH}_{\text{ijk}} = \pi_{0\text{jk}} + e_{\text{ijk.}}$$

School-Level (Level 2) Model:

$$\pi_{0\text{jk}} = \beta_{00\text{k}} + \gamma_{0\text{jk.}}$$

Country-Level (Level 3) Model:

$$\beta_{00\text{k}} = \gamma_{000} + \gamma_{001}(OECD_k) + \gamma_{002}(STRICT_k) + \gamma_{003}(GDP_k) + \gamma_{004}(GG_k) + \gamma_{005}(GINI_k) + \gamma_{006}(YRURAL_k) + \gamma_{007}(YCITY_k) + \gamma_{008}(YPRIV_k) + \gamma_{009}(YSTR_k) + \gamma_{0010}(YPFCT_k) + \gamma_{0011}(YCSIZE_k) + \gamma_{0012}(YCREA_k) + \gamma_{0013}(YSBHL_k) + \gamma_{0014}(YTBHL_k) + u_{00\text{k.}}$$

Since this model was also a means-as-outcomes model, all the level 3 predictors were grand mean centered. As shown in the Table 4.4, the strict university admission system (STRICT) (γ_{002}=51.52, p$\leq$ 0.001) still had a positive association with country-mean math achievement (YPM1 to YPM10). However, the GDP per capita (GDP) and the GINI Index (GINI) variable were no longer statistically significant in this model. Meanwhile, the variable indicating OECD member (OECD) (γ_{001}=32.46, p$\leq$ 0.01) had a positive association with country-mean math achievement after controlling for nine school-level compositional variables. There was a increase in coefficients of the predictor had a statistically significant association with the dependent variable after controlling for school-level compositional variables. The coefficient for types of university admissions (STRICT) (γ_{002}) increased from 47.63 to 51.52.

As shown in the Table 4.4, several compositional variables created by aggregating the school-level variables had statistically positive significant associations with the dependent variable, country-mean math achievement. The variable indicating country-mean of student-teacher ratio (YSTR) had a negative association with country-mean math achievement (γ_{009}= -481.79, p$\leq$ 0.001). Meanwhile, the country-mean proportion of fully certified teachers (YPFCT) had a positive relationship with country-mean math achievement (γ_{010}= 104.82, p$\leq$ 0.001). The results of the model also showed that the country-mean extra-curricular activities in school (YCREA) had a positive association with country-mean math achievement (γ_{0012}= 33.22, p$\leq$ 0.05) while student behavior hindering learning (YSBHL) (γ_{0012}= -0.81, p$\leq$ 0.01).

The results of the amount of variance explained at each level is described in the Table 4.5. As shown in the table, the level-3 pseudo-R^2 (${R^2}_{L-3}$) for Model 2-B was 87.07%. This result means that 87.07% of the country-level variance for country-mean math achievement was explained by 14 predictors (OECD, STRICT, GDP, GG, GINI, YRURAL, YCITY, YPRIV, YSTR, YPFCT, YCSIZE, YCREA, YSBHL, and YTBHL) in this model. After removing effects of the 14 predictors, the correlation between pairs of scores in the same country, which had been 31.30% in the null model, is reduced by 5.56%.

Model 2-C: Country-level main predictors with all compositional variables model

In the model 2-C, all country-level predictors including compositional variables obtained by aggregating student-level variables and school-level variables were added. Five country-level variables (OECD, STRICT, GDP, GG, and GINI), nine compositional variables (YRURAL, YCITY, YPRIV, YSTR, YPFCT, YCSIZE, YCREA, YSBHL, and YTBHL) that were created by aggregating school-level variables, and 11 compositional variables (YFEM, YPARED, YICT, YPARES, YBELN, YRSELF, YMAG, YFFAIL, YOA, YVSCH, and YGM) obtained by aggregating student-level variables were added to this model. Equations for this model are as follow:

Equation 4. *Equations for Country-level Main Predictors with All Compositional Variables (Model2-C)*

Student-Level (Level 1) Model:

$$PVMATH_{\mathrm{ijk}}= \pi_{0\mathrm{jk}} + e_{\mathrm{ijk.}}$$

School-Level (Level 2) Model:

$$\pi_{0jk} = \beta_{00k} + \gamma_{0jk.}$$

Country-Level (Level 3) Model:

$$\beta_{00k} = \gamma_{000} + \gamma_{001}(OECD_k) + \gamma_{002}(STRICT_k) + \gamma_{003}(GDP_k) + \gamma_{004}(GG_k) + \gamma_{005}(GINI_k) + \gamma_{006}(YRURAL_k) + \gamma_{007}(YCITY_k) + \gamma_{008}(YPRIV_k) + \gamma_{009}(YSTR_k) + \gamma_{0010}(YPFCT_k) + \gamma_{0011}(YCSIZE_k) + \gamma_{0012}(YCREA_k) + \gamma_{0013}(YSBHL_k) + \gamma_{0014}(YTBHL_k) + \gamma_{0015}(YFEM_k) + \gamma_{0016}(YPARED_k) + \gamma_{0017}(YICT_k) + \gamma_{0018}(YPARES_k) + \gamma_{0019}(YBELN_k) + \gamma_{0020}(YRSELF_k) + \gamma_{0021}(YMAG_k) + \gamma_{0022}(YFFAIL_k) + \gamma_{0023}(YOA_k) + \gamma_{0024}(YVSCH_k) + \gamma_{0025}(YGM_k) + u_{00k.}$$

The results of the model found that there were several variables that had a statistically significant positive association with country-mean math achievement. The variable STRICT (γ_{002}=31.84, p$\leq$ 0.05) identifying types of university admission procedure (1=strict, 0=flexible), country-mean student behavior hindering learning (YSBHL) (γ_{0013}=32.88, p$\leq$ 0.05), country-mean teacher behavior hindering learning (YTBHL) (γ_{0014}=43.64, p$\leq$ 0.001), and country-mean ICT usage (YICT) (γ_{0017}=34.99, p$\leq$ 0.05) had a positive association with country-mean math achievement. The results mean that there was a unit increase in these variables, there was an increase in country-mean mathematics achievement after controlling for other predictors in the model.

There were two variables that had a statistically significant negative association with country-mean math achievement. The country-mean parental education level (YPARED) (γ_{0016}=-9.57, p$\leq$ 0.05) and country-mean resilience self-efficacy (YRSELF) (γ_{020}=-107.15, p$\leq$ 0.001) had a negative association. In the marginal correlation between the country-mean parental education level (YPARED) and the country-mean math achievement (YPVMATH1) was positive. However, this positive correlation between the two variables was reversed in the Model-2C. This means that when all other predictors were controlled, countries that have higher parental education level show lower country math achievement. This situation in which a relationship observed at the group reverse is known as Simpson's paradox (Blyth, 1972). In order to find predictors that make reverse the sign of correlation between the country-mean parental education level (YPARED) and the country-mean math achievement (YPVMATH1), at each step gradually eliminated variables from the model and then the country-mean ICT usage was the strongest variable that reversed the sign of the YPARED coefficient. This can be interpretated that the relationship between the country-mean parental education level (YPARED) and the country-mean math achievement (YPM1) is positive while controlling for the effect of country-mean ICT usage. There was no statistically significant association between country-mean growth mindset (YGM) which was one of main interests and country-mean math achievement.

The results of the amount of variance explained at each level is described in the Table 4.5. As shown in the table, the level-3 pseudo-R^2 (R^2_{L-3}) for Model 2-C was 93.15%. This result means that 93.15% of the country-level variance for country-mean math achievement was explained by level 3 predictors in this model. However, there are still 6.85% of variability of mean math achievement across countries cannot be explained by this model. After removing effects of the 25 predictors, the correlation between pairs of scores in the same country, which had been 31.30% in the null model, is reduced by 3.03%.

Model 3-A: School-level main predictors without compositional variables model

In response to the third research question, the Model3-A was estimated. This model was constructed with school-related variables (school locale, type of school, student-teacher ratio, proportion of fully certified teachers, class size, extra-curricular activities in school, student behavior hindering learning, and teacher behavior hindering learning). The equations of the model are as follows:

Equation 5. *Equations for School-level Main Predictors Without Compositional Variables Model (Model3-A)*

Student-Level (Level 1) Model:

$\mathrm{PVMATH}_{\mathrm{ijk}} = \pi_{0\mathrm{jk}} + e_{\mathrm{ijk}}$.

School-Level (Level 2) Model:

$\pi_{0\mathrm{jk}} = \beta_{00\mathrm{k}} + \beta_{01\mathrm{k}}\,(RURAL_{jk}) + \beta_{02\mathrm{k}}\,(CITY_{jk}) + \beta_{03\mathrm{k}}\,(PRIV_{jk}) + \beta_{04\mathrm{k}}\,(STR_{jk}) + \beta_{05\mathrm{k}}\,(PFCT_{jk}) + \beta_{06\mathrm{k}}\,(CSIZE_{jk}) + \beta_{07\mathrm{k}}\,(CREA_{jk}) + \beta_{08\mathrm{k}}\,(SBHL_{jk}) + \beta_{09\mathrm{k}}\,(TBHL_{jk}) + \gamma_{0\mathrm{jk}}$.

Country-Level (Level 3) Model:

$\beta_{00\mathrm{k}} = \gamma_{000} + u_{00\mathrm{k}}$
$\beta_{01\mathrm{k}} = \gamma_{010}$
$\beta_{02\mathrm{k}} = \gamma_{020}$
$\beta_{03\mathrm{k}} = \gamma_{030}$
$\beta_{04\mathrm{k}} = \gamma_{040}$
$\beta_{05\mathrm{k}} = \gamma_{050}$
$\beta_{06\mathrm{k}} = \gamma_{060}$
$\beta_{07\mathrm{k}} = \gamma_{070}$
$\beta_{08\mathrm{k}} = \gamma_{080}$
$\beta_{09\mathrm{k}} = \gamma_{090}$

The level-2 predictors were group mean centered and this model is called as the group mean centering model or fixed effects (FE) model (in economics). This model centered the school-level predictors around their corresponding school-level unit means. In the case of the model, the intercept $\beta_{00\mathrm{k}}$ becomes the unadjusted mean for group k. That is $\beta_{00\mathrm{k}} = \mu_{\mathrm{PVMATH_k}}$, which represents the population mean for mean for country k for mathematics achievement. Also, Var ($\beta_{00\mathrm{k}}$) is just the variance among the level-3 unit means, $\mu_{\mathrm{PVMATH_k}}$. As shown in the Table 4.5, the level 1 error variance (σ^2= 4507.66) and the level 3 error variance ($\tau_\beta = 3230.66$) were estimated almost the same as the values in the fully unconditional model (Model-1). This means that adding level 2 predictors by group mean centering only explains level 2 variance not level 3 and level 1. Accordingly, γ_{010}, γ_{020}, γ_{030}, γ_{040}, γ_{050}, γ_{060}, γ_{070}, γ_{080}, and γ_{090} describe the pure (i.e., not overlapped with relationship with other level) relationship between the school-level predictors and math achievement within that country. Also, slopes for RURAL ($\beta_{01\mathrm{k}}$),

CITY (β_{02k}), PRIV (β_{03k}), STR (β_{04k}), PFCT (β_{05k}), CSIZE (β_{06k}), CREA (β_{07k}), SBHL (β_{08k}), and TBHL (β_{09k}) were fixed since these within-country slopes were assumed equal.

As shown in the Table 4.4, this model found several variables were significant at school-level. The variable indicating that the school is in rural areas (rural = 1, not rural = 0) was found to have a statistically negative association with school-mean student mathematics achievement (XPM1 to XPM10) (γ_{010}= -20.76, p$\leq$ 0.001) while the variable indicating that the school is in city had a positive association with student mathematics achievement (γ_{020}= 10.59, p$\leq$ 0.01). The results indicate that there is a significant difference of math achievement between students in rural and city schools even after controlling for other school-related predictors. That is to say, the geographical location of schools has a significant association with student math achievement. Student math achievement in the school located in a city is higher than those in a rural area. Also, private schools (PRIV) scored significantly higher in math achievement than public schools (γ_{030}= 25.25, p$\leq$ 0.001). School class size (CSIZE) had a statistically significant positive association with students' math achievement (γ_{060}= 0.52, p$\leq$ 0.001). This shows that students in larger classes perform better in math compared to peers in smaller classes after controlling for other predictors in this model. The result of the model also shows that extra-curricular activities in school (CREA) had a statistically significant positive association with math achievement (γ_{070}= 9.05, p$\leq$ 0.001), which means that students in schools that provide more extracurricular activities such as music and art activities perform better in mathematics. Also, the student behavior hindering learning (SBHL) variable had a statistically significant negative association with students 'math achievement (γ_{080}= -11.82, p$\leq$ 0.001). This indicates schools are led by school principals who perceive student-related factors may hinder students' learning more heavily influence on students' learning show lower students' math achievement.

On the other hand, the teacher behavior hindering learning (TBHL) variable was shown to have a positive association with math achievement (γ_{090}= 4.60, p$\leq$ 0.05) after controlling for other predictors in this model. This result indicates that schools are led by school principals who think teacher-related factors that might hinder the learning climate have stronger impact on students' learning show higher students' math achievement. However, this result seems counter-intuitive because it is contrary to common-sense expectation.

The results of the amount of variance explained at each level is described in the Table 4.5. As shown in the table, the level-2 pseudo-R^2 (R^2_{L-2}) for Model 3-A was 22.97%. This result means that 22.97% of the school-level variance for school-mean math achievement was explained by level 2 predictors in this model. In addition, level-1 error variance (σ^2) and level-3 error variance (τ_β) were estimated as the almost same values as values in the null model (Model 1) which means that level-2 predictors explained the level-2 variance, but not level-1 and level-3 variance.

Model 3-B: School-level main predictors with compositional variables model

In the model 3-B, compositional variables were added to the previous model (Model 3-A). The compositional variables were created by aggregating student-level variables and include the proportion of female in school (XFEM), school-mean parental education level (XPARED), school-mean ICT usage (XICT), school-mean parents' emotional support (XPARES), school-mean sense of belonging in school (XBELN), school-mean resilience self-efficacy (XRSELF), school-mean mastery goal orientation (XMAG), school-mean fear of failure (XFFAIL), and school-mean occupational aspiration (XOA), school-mean belief in the value of school (XVSCH), school-mean growth mindset (XGM). This model is also FE model and all variables at school-level (level 2) were group-mean centered. Also, slopes for RURAL ($\beta_{01\mathrm{k}}$), CITY

(β_{02k}), PRIV (β_{03k}), STR (β_{04k}), PFCT (β_{05k}), CSIZE (β_{06k}), CREA (β_{07k}), SBHL (β_{08k}), TBHL (β_{09k}), XFEM (β_{010k}), XPARED (β_{011k}), XICT (β_{012k}), XPARES (β_{013k}), XBELN (β_{014k}), XRSELF (β_{015k}), XMAG (β_{016k}), XFFAIL (β_{017k}), XOA (β_{018k}), XVSCH (β_{019k}), XGM (β_{020k}) were fixed since these within-country slopes were assumed equal. The equations of the model are as follows:

Equation 6. *Equations for School-level Main Predictors with Compositional Variables Model (Model3-B)*

Student-Level (Level 1) Model:

$$\mathrm{PVMATH_{ijk}} = \pi_{\mathrm{0jk}} + e_{\mathrm{ijk}}.$$

School-Level (Level 2) Model:

$$\pi_{\mathrm{0jk}} = \beta_{\mathrm{00k}} + \beta_{\mathrm{01k}}\,(RURAL_{jk}) + \beta_{\mathrm{02k}}\,(CITY_{jk}) + \beta_{\mathrm{03k}}\,(PRIV_{jk}) + \beta_{\mathrm{04k}}\,(STR_{jk}) + \beta_{\mathrm{05k}}\,(PFCT_{jk}) + \beta_{\mathrm{06k}}\,(CSIZE_{jk}) + \beta_{\mathrm{07k}}\,(CREA_{jk}) + \beta_{\mathrm{08k}}\,(SBHL_{jk}) + \beta_{\mathrm{09k}}\,(TBHL_{jk}) + \beta_{\mathrm{010k}}\,(XFEM_{jk}) + \beta_{\mathrm{011k}}\,(XPARED_{jk}) + \beta_{\mathrm{012k}}\,(XICT_{jk}) + \beta_{\mathrm{013k}}\,(XPARES_{jk}) + \beta_{\mathrm{014k}}\,(XBELN_{jk}) + \beta_{\mathrm{015k}}\,(XRSELF_{jk}) + \beta_{\mathrm{016k}}\,(XMAG_{jk}) + \beta_{\mathrm{017k}}\,(XFFAIL_{jk}) + \beta_{\mathrm{018k}}\,(XOA_{jk}) + \beta_{\mathrm{019k}}\,(XVSCH_{jk}) + \beta_{\mathrm{020k}}\,(XGM_{jk}) + \gamma_{\mathrm{0jk}}.$$

Country-Level (Level 3) Model:

$$\beta_{\mathrm{00k}} = \gamma_{000} + u_{\mathrm{00k}}$$
$$\beta_{\mathrm{01k}} = \gamma_{010}$$
$$\beta_{\mathrm{02k}} = \gamma_{020}$$
$$\beta_{\mathrm{03k}} = \gamma_{030}$$
$$\beta_{\mathrm{04k}} = \gamma_{040}$$
$$\beta_{\mathrm{05k}} = \gamma_{050}$$
$$\beta_{\mathrm{06k}} = \gamma_{060}$$
$$\beta_{\mathrm{07k}} = \gamma_{070}$$
$$\beta_{\mathrm{08k}} = \gamma_{080}$$
$$\beta_{\mathrm{09k}} = \gamma_{090}$$
$$\beta_{\mathrm{010k}} = \gamma_{0100}$$
$$\beta_{\mathrm{011k}} = \gamma_{0110}$$
$$\beta_{\mathrm{012k}} = \gamma_{0120}$$
$$\beta_{\mathrm{013k}} = \gamma_{0130}$$
$$\beta_{\mathrm{014k}} = \gamma_{0140}$$
$$\beta_{\mathrm{015k}} = \gamma_{0150}$$
$$\beta_{\mathrm{016k}} = \gamma_{0160}$$
$$\beta_{\mathrm{017k}} = \gamma_{0170}$$
$$\beta_{\mathrm{018k}} = \gamma_{0180}$$

$\beta_{019k} = \gamma_{0190}$
$\beta_{020k} = \gamma_{0200}$

As shown in the Table 4.4, this model found several variables from Model 3-A were still significant at school-level after controlling for student-level compositional variables. The RURAL, CSIZE, CREA, and SBHL still had statistically significant association with school-mean math achievement, but the coefficients' power were reduced. The power of coefficient for the variable indicating school locale (RURAL) was decreased from -20.76 to -6.86, for class size variable (CSZIE) decreased from 0.52 to 0.21, for extra-curricular activities in school (CREA) decreased from 9.05 to 4.30 and for student behavior hindering learning (SBHL) decreased from -11.82 to -6.66. Meanwhile, the variable indicating school locale (PRIV) and student-teacher ratio (STR) were no longer statistically significant after controlling for variables in this model.

Among compositional variables created by aggregating student-level variables, school level ICT usage (XICT) (γ_{0120}= 0.23, p$\leq$ 0.001), school-mean parents' emotional support (XPARES) (γ_{0130}= 23.61, p$\leq$ 0.001), school-mean sense of belonging in school (XBELN) (γ_{0140}= 18.44, p$\leq$ 0.05), school-mean occupational aspiration (XOA) (γ_{0180}= 7.95, p$\leq$ 0.001), and school-mean growth mindset (XGM) (γ_{0200}= 9.28, p$\leq$ 0.001) had a positive association with school-mean mathematics achievement (XPM1 to XPM10).

The results of the amount of variance explained at each level is described in the Table 4.5. As shown in the table, the level-2 pseudo-R^2 (R^2_{L-2}) for Model 3-B was 50.88%. This result means that 50.88% of the school-level variance for school-mean math achievement was explained by level 2 predictors in this model. In addition, level-1 error variance (σ^2) was estimated as the almost same value as values in the null model (Model 1) which means that level-2 predictors explained the level-2 variance, but not level-1. However, level-3 error variance

(τ_{β}) was estimated 498.38 difference in value in the null model (Model 1) and this can be interpreted that level-2 predictors can also be explained level-3 variance in this model.

Model 4: Student-level predictors model

In response to the fourth research question, the Model 4 was estimated. After completing Model 3-A and 3-B, student-level (level 1) predictors were fitted to the model. All student-level (level 1) predictors were group-mean centered to examine pure relationship between the predictors and student math achievement. Group-mean centering level-1 predictors can examine pure level-1 effects without considering level-2 and level-3 variables. Student-level predictors included female indicator (FEM), parental education level (PARED), ICT usage (ICT), parents' emotional support (PARES), sense of belonging in school (BELN), resilience self-efficacy (RSELF), mastery goal orientation (MAG), fear of failure (FFAIL), occupational aspiration (OA), belief in the value of school (VSCH), and growth mindset (GM). Also, slopes for student-level variables were fixed. The equations of the model are as follows:

Equation 7. *Equations for Student-level Predictors Model (Model 4)*

Student-Level (Level 1) Model:

$$\mathrm{PVMATH_{ijk}} = \pi_{0\mathrm{jk}} + \pi_{1\mathrm{jk}}\,(FEM_{ijk}) + \pi_{2\mathrm{jk}}\,(PARED_{ijk}) + \pi_{3\mathrm{jk}}\,(ICT_{ijk}) + \pi_{4\mathrm{jk}}\,(PARES_{ijk}) + \pi_{5\mathrm{jk}}\,(BELN_{ijk}) + \pi_{6\mathrm{jk}}\,(RSELF_{ijk}) + \pi_{7\mathrm{jk}}\,(MAG_{ijk}) + \pi_{8\mathrm{jk}}\,(FFAIL_{ijk}) + \pi_{9\mathrm{jk}}\,(OA_{ijk}) + \pi_{10\mathrm{jk}}\,(VSCH_{ijk}) + \pi_{11\mathrm{jk}}\,(GM_{ijk}) + e_{\mathrm{ijk}}$$

School-Level (Level 2) Model:

$$\pi_{0\mathrm{jk}} = \beta_{00\mathrm{k}} + \gamma_{0\mathrm{jk}}$$
$$\pi_{1\mathrm{jk}} = \beta_{10\mathrm{k}}$$
$$\pi_{2\mathrm{jk}} = \beta_{20\mathrm{k}}$$
$$\pi_{3\mathrm{jk}} = \beta_{30\mathrm{k}}$$
$$\pi_{4\mathrm{jk}} = \beta_{40\mathrm{k}}$$
$$\pi_{5\mathrm{jk}} = \beta_{50\mathrm{k}}$$
$$\pi_{6\mathrm{jk}} = \beta_{60\mathrm{k}}$$
$$\pi_{7\mathrm{jk}} = \beta_{70\mathrm{k}}$$
$$\pi_{8\mathrm{jk}} = \beta_{80\mathrm{k}}$$
$$\pi_{9\mathrm{jk}} = \beta_{90\mathrm{k}}$$

$\pi_{10jk} = \beta_{100k}$
$\pi_{11jk} = \beta_{110k}$

Country-Level (Level 3) Model:

$\beta_{00k} = \gamma_{000} + u_{00k}$
$\beta_{10k} = \gamma_{100}$
$\beta_{20k} = \gamma_{200}$
$\beta_{30k} = \gamma_{300}$
$\beta_{40k} = \gamma_{400}$
$\beta_{50k} = \gamma_{500}$
$\beta_{60k} = \gamma_{600}$
$\beta_{70k} = \gamma_{700}$
$\beta_{80k} = \gamma_{800}$
$\beta_{90k} = \gamma_{900}$
$\beta_{100k} = \gamma_{1000}$
$\beta_{110k} = \gamma_{1100}$

The results from Table 4.4 show that there were six student-level variables are statistically significant. In the model, student's gender (FEM) (γ_{100}= -8.70, $p \leq 0.001$), ICT usage (ICT) (γ_{300}= 5.49, $p \leq 0.001$), parents' emotional support (PARES) (γ_{400}= 3.86, $p \leq 0.001$), mastery goal orientation (MAG) (γ_{700}= 1.32, $p \leq 0.05$), occupational aspiration (OA) (γ_{900}= 8.81, $p \leq 0.001$), and growth mindset (GM) (γ_{110}= 8.15, $p \leq 0.001$), were found to be statistically significant. The variable indicating students' gender (FEM) was found to have negative association with math achievement (PVMATH) This means that female students perform lower than male students in mathematics. In this model, the group-mean centering (fixed effects) model was used to examine that the effects of student-level predictors without considering the effects of school- and country-level predictors. Therefore, the results of this model indicate that the effects of gender, ICT usage, parents' emotional support, mastery goal orientation, occupational aspiration, and growth mindset exist universally regardless of the school and country contexts.

The results of the amount of variance explained at each level is described in the Table 4.5. As shown in the table, the level-1 pseudo-R^2 (R^2_{L-2}) for Model 4 was 4.35%. This value indicates that 4.36% of the original student-level variance for math achievement score was explained by gender, parental education level, ICT usage, parents' emotional support, sense of belonging in school, resilience self-efficacy, mastery goal orientation, fear of failure, occupational aspiration, belief in the value of school, and growth mindset.

Model 5: Final model

In response to the final research question, the final model was built by adding all student-level, school-level, and country-level predictors. All the predictors entered the country-level (level 3) can only be centered at grand-mean because there is no higher-level group in this model. Centering around grand mean at level 3 allows us to improve the interpretation of the intercept values. Predictors variables that were grand mean centered have the same values as the original predictors' values. The country-level predictor coefficients (γ_{00k}) indicate between-country effect. All the student-level (level 1) and school-level (level 3) variables were group-mean centered. When group-mean centering of the student-level predictors is used, the student-level predictor coefficients (γ_{k00}) represent within-school effects and the school-level predictor coefficients (γ_{0k0}) represent within-country effects.

Compositional of contextual effect mean differences between the effects of cluster mean predictors and their individual-level predictors. In other words, Compositional effects take place when the aggregate of an individual-level characteristic is associated with the outcome even after controlling for the individual characteristics (Bryk & Raudenbush, 1992). In this study, compositional variables at school-level and country-level were extracted from student-level variables to examine school and country compositional effects. Compositional effects at school-level can be estimated by calculating the difference between the school-level relationship and student-level effects, while compositional effects at country-level can be estimated by calculating the difference between the country-level relationship and student-level effects. The equations for the final model are as follows:

Equation 8. *Equations for Final Model (Model 5)*

Student-Level (Level 1) Model:

$\mathrm{PVMATH}_{\mathrm{ijk}} = \pi_{0\mathrm{jk}} + \pi_{1\mathrm{jk}}\,(FEM_{ijk}) + \pi_{2\mathrm{jk}}\,(PARED_{ijk}) + \pi_{3\mathrm{jk}}\,(ICT_{ijk}) + \pi_{4\mathrm{jk}}\,(PARES_{ijk}) + \pi_{5\mathrm{jk}}\,(BELN_{ijk}) + \pi_{6\mathrm{jk}}\,(RSELF_{ijk}) + \pi_{7\mathrm{jk}}\,(MAG_{ijk}) + \pi_{8\mathrm{jk}}\,(FFAIL_{ijk}) + \pi_{9\mathrm{jk}}\,(OA_{ijk}) + \pi_{10\mathrm{jk}}\,(VSCH_{ijk}) + \pi_{11\mathrm{jk}}\,(GM_{ijk}) + e_{\mathrm{ijk}}$

School-Level (Level 2) Model:

$\pi_{0\mathrm{jk}} = \beta_{00\mathrm{k}} + \beta_{01\mathrm{k}}\,(RURAL_{jk}) + \beta_{02\mathrm{k}}\,(CITY_{jk}) + \beta_{03\mathrm{k}}\,(PRIV_{jk}) + \beta_{04\mathrm{k}}\,(STR_{jk}) + \beta_{05\mathrm{k}}\,(PFT_{jk}) + \beta_{06\mathrm{k}}\,(CSIZE_{jk}) + \beta_{07\mathrm{k}}\,(CREA_{jk}) + \beta_{08\mathrm{k}}\,(SBHL_{jk}) + \beta_{09\mathrm{k}}\,(TBHL_{jk}) + \beta_{010\mathrm{k}}\,(XFEM_{jk}) + \beta_{011\mathrm{k}}\,(XPARED_{jk}) + \beta_{012\mathrm{k}}\,(XICT_{jk}) + \beta_{013\mathrm{k}}\,(XPARES_{jk}) + \beta_{014\mathrm{k}}\,(XBELN_{jk}) + \beta_{015\mathrm{k}}\,(XRSELF_{jk}) + \beta_{016\mathrm{k}}\,(XMAG_{jk}) + \beta_{017\mathrm{k}}\,(XFFAIL_{jk}) + \beta_{018\mathrm{k}}\,(XOA_{jk}) + \beta_{019\mathrm{k}}\,(XVSCH_{jk}) + \beta_{020\mathrm{k}}\,(XGM_{jk}) + \gamma_{0\mathrm{jk}}.$

$\pi_{1\mathrm{jk}} = \beta_{10\mathrm{k}}$

$\pi_{2\mathrm{jk}} = \beta_{20\mathrm{k}}$

$\pi_{3\mathrm{jk}} = \beta_{30\mathrm{k}}$

$\pi_{4\mathrm{jk}} = \beta_{40\mathrm{k}}$

$\pi_{5\mathrm{jk}} = \beta_{50\mathrm{k}}$

$\pi_{6\mathrm{jk}} = \beta_{60\mathrm{k}}$

$\pi_{7\mathrm{jk}} = \beta_{70\mathrm{k}}$

$\pi_{8\mathrm{jk}} = \beta_{80\mathrm{k}}$

$\pi_{9\mathrm{jk}} = \beta_{90\mathrm{k}}$

$\pi_{10\mathrm{jk}} = \beta_{100\mathrm{k}}$

$\pi_{11\mathrm{jk}} = \beta_{110\mathrm{k}}$

Country-Level (Level 3) Model:

$\beta_{00\mathrm{k}} = \gamma_{000} + \gamma_{001}(OECD_k) + \gamma_{002}(STRICT_k) + \gamma_{003}(GDP_k) + \gamma_{004}(GG_k) + \gamma_{005}(GINI_k) + \gamma_{006}(YRURAL_k) + \gamma_{007}(YCITY_k) + \gamma_{008}(YPRIV_k) + \gamma_{009}(YSTR_k) + \gamma_{010}(YPFT_k) + \gamma_{011}(YCSIZE_k) + \gamma_{012}(YCREA_k) + \gamma_{013}(YSBHL_k) + \gamma_{014}(YTBHL_k) + \gamma_{015}(YFEM_k) + \gamma_{016}(YPARED_k) + \gamma_{017}(YICT_k) + \gamma_{018}(YPARES_k) + \gamma_{019}(YBELN_k) + \gamma_{020}(YRSELF_k) + \gamma_{021}(YMAG_k) + \gamma_{022}(YFFAIL_k) + \gamma_{023}(YOA_k) + \gamma_{024}(YVSCH_k) + \gamma_{025}(YGM_k) + u_{00\mathrm{k}}.$

$\beta_{01\mathrm{k}} = \gamma_{010}$

$\beta_{02\mathrm{k}} = \gamma_{020}$

$\beta_{03k} = \gamma_{030}$
$\beta_{04k} = \gamma_{040}$
$\beta_{05k} = \gamma_{050}$
$\beta_{06k} = \gamma_{060}$
$\beta_{07k} = \gamma_{070}$
$\beta_{08k} = \gamma_{080}$
$\beta_{09k} = \gamma_{090}$
$\beta_{010k} = \gamma_{0100}$
$\beta_{011k} = \gamma_{0110}$
$\beta_{012k} = \gamma_{0120}$
$\beta_{013k} = \gamma_{0130}$
$\beta_{014k} = \gamma_{0140}$
$\beta_{015k} = \gamma_{0150}$
$\beta_{016k} = \gamma_{0160}$
$\beta_{017k} = \gamma_{0170}$
$\beta_{018k} = \gamma_{0180}$
$\beta_{019k} = \gamma_{0190}$
$\beta_{020k} = \gamma_{0200}$
$\beta_{10k} = \gamma_{100}$
$\beta_{20k} = \gamma_{200}$
$\beta_{30k} = \gamma_{300}$
$\beta_{40k} = \gamma_{400}$
$\beta_{50k} = \gamma_{500}$
$\beta_{60k} = \gamma_{600}$
$\beta_{70k} = \gamma_{700}$
$\beta_{80k} = \gamma_{800}$
$\beta_{90k} = \gamma_{900}$
$\beta_{100k} = \gamma_{1000}$
$\beta_{110k} = \gamma_{1100}$

This model found four compositional effects at school-level. First, the ICT usage variable had compositional effect at school-level. The student-level ICT usage (ICT) effect was 5.49, the school-level ICT usage (XICT) effect was 23.55, and the difference between those two was 18.06. This illustrates that the expected deference in math achievement between students who have the same ICT usage, but who belong to schools differing by one unit in mean ICT usage was 18.06. The second compositional effect at school-level was parents' emotional support. The student-level parents' emotional support (PARES) effect was 18.43, the school-level parents' emotional support (XPARES) was 3.86, and the difference between those two was 14.57. This indicates that if two students who have the same parents' emotional support but attend schools differing by one unit in mean parents' emotional support, the math achievement score difference will be 14.57. Third, the occupational aspiration variable had a compositional effect at school-level. The student-level occupational aspiration (OA) effect was 8.81, the school-level occupational aspiration (XOA) was 24.11, and the difference between these two, the occupational aspiration compositional effect, was 15.30. This implies that the expected difference in math achievement between two students who have same occupational aspirations but belong to schools differing by one unit in mean occupational aspiration is 15.30. The last compositional effect at school-level was growth mindset. The student-level growth mindset effect (GM) was 8.15 while the school-level growth mindset effect (XGM) was 23.37, and the differences between these two was 15.22. This means that the expected difference in math achievement between two students who have same occupational aspirations but belong to schools differing by one unit in mean growth mindset is 15.22.

This model also found a compositional effect at country-level. The compositional effect was found from ICT usage variable. The student-level ICT usage (ICT) effect was 5.49, the country-level ICT usage (YICT) effect was 35.44, and the difference between those two was 29.95. This indicates that the expected difference in math achievement between two students who have the ICT usage, but who are in different countries differing by one unit in country-mean ICT usage level is 29.95.

Other than examining compositional effects, the final model found that there were several variables that had a statistically significant positive association with student's math achievement. At country-level, the strict university admission system (STRICT) (γ_{002} = 25.89, p$\leq$ 0.05), the country-mean city (YCITY) (γ_{007} = 94.02, p$\leq$ 0.05), country-mean proportion of fully certified teacher (YPFCT) (γ_{0010} = 56.67, p≤ 0.05), country-mean teacher behavior hindering learning (YTBHL) (γ_{0014} = 36.61, p≤ 0.001), and country-mean ICT usage (YICT) (γ_{0017} = 35.44, p≤ 0.01), were positively association with math achievement. At school-level, extra-curricular activities in school (CREA) (γ_{070} = 4.27, p≤ 0.01), school-mean ICT usage (XICT) (γ_{0120} = 23.55, p≤ 0.001), school-mean parents' emotional support (XPARES) (γ_{0130} = 18.43, p≤ 0.001), school-mean sense of belonging in school (XBELN) (γ_{0140} = 12.92, p≤ 0.01), school-mean occupational aspiration (XOA) (γ_{0180} = 24.11, p≤ 0.001), and school-mean growth mindset (XGM) (γ_{0200} = 23.37, p≤ 0.001) were positively association with math achievement. At student-level, ICT usage (ICT) (γ_{300} = 5.49, p≤ 0.001), parents' emotional support (PARES) (γ_{400} = 3.86, p≤ 0.001), resilience self-efficacy (RSELF) (γ_{600} = 2.45, p≤ 0.01), , occupational aspiration (OA) (γ_{900} = 8.81, p≤ 0.001), and growth mindset (GM) (γ_{1100} = 8.15, p≤ 0.001) were positively association with math achievement.

The final model also found several variables that had a negative association with math achievement. At country-level, country-mean student-teacher ratio (YSTR) (γ_{009} = -366.09, p≤ 0.01), country-mean parental education level (YPARED) (γ_{0016} = -14.45, p≤ 0.01), and country-mean resilience self-efficacy (YSELF) (γ_{0020} = -105.90, p≤ 0.01) were negatively association with math achievement. At school-level, the variable indication school in rural (XRURAL) (γ_{010} = -6.92, p≤ 0.05) and student behavior hindering learning (SBHL) (γ_{080} = -6.65, p≤ 0.001) were negatively association with math achievement. At student-level, only the variable indicating female (FEM) (γ_{100} = -8.69, p≤ 0.01) was negatively association with math achievement.

To compare student-, school-, and country-level effects more directly, the raw regression coefficients were converted to half- and completely standardized regression coefficients. Comparing unstandardized regression coefficients may not be very meaningful since the coefficients only present the expected change in the outcome variable for a unit change in the predictor variable and this change cannot be directly comparable since it's not scaled. Therefore, half- and completely standardized regression coefficients using the standard deviations should be examined for scale free within- and between-level comparison. The results of half- and completely standardized regression coefficients are reported in Table 4.6 and the results of this table are described in more detail in Chapter 5. In addition, the final model found several predictors statistically significant negative association with math achievement. The results were counterintuitive to the general expectations, which requires some investigations for explanation of why that happened. Therefore, I attempted to provide a explanation for the counterintuitive results using graphical methods. Detailed interpretation and explanations about the counterintuitive results are discussed in Chapter 5.

Table 4. 4. *Results of HLM Analysis*

	Model-1	Model-2A	Model2-B	Model2-C	Model-3A	Model3-B	Model 4	Model 5
Fixed Effects								
Country-level								
Intercept, γ_{000}	417.49***	439.17***	441.23***	441.48***	423.78***	429.85***	417.45***	450.11***
OECD country, γ_{001}		-9.70	32.46*	17.57				18.02
Strict University Admission System, γ_{002}		47.63	51.52***	31.84**				25.89*
GDP per Capita, γ_{003}		25.00***	4.40	2.72				1.01
Gender Inequality, γ_{004}		-133.98	83.97	166.92				153.97
GINI Index, γ_{005}		276.28	14.91	16.32				68.30
Country-mean Rural, γ_{006}			23.58	91.35				92.12
Country-mean City, γ_{007}			70.95	86.00				94.02*
Country-mean Private School, γ_{008}			-35.04	39.00				33.15
Country-mean Student-Teacher Ratio, γ_{009}			-481.79**	-445.45**				-366.06**
Country-mean Proportion of Fully Certified Teachers, γ_{0010}			104.82**	50.58				56.67*
Country-mean Class Size, γ_{0011}			-1.32	0.94				-0.20
Country-mean Extra-Curricular Activities in School, γ_{0012}			33.22*	-25.17				-13.93
Country-mean Student Behavior Hindering Learning, $\gamma 0_{013}$			-0.81	32.88*				24.42
Country-mean Teacher Behavior Hindering Learning, γ_{0014}			34.32**	43.64***				36.61***
Country-mean Female, γ_{0015}				-441.93				-263.69
Country-mean Parental Education Level, γ_{0016}				-9.57*				-14.45**
Country-mean ICT usage, γ_{0017}				34.99*				35.44**
Country-mean Parents Emotional Support, γ_{0018}				-25.26				5.35
Country-mean Sense of Belonging, γ_{0019}				41.74				48.37
Country-mean Resilience Self-efficacy, γ_{0020}				-107.15**				-105.90**
Country-mean Mastery Goal Orientation, γ_{0021}				29.39				24.23
Country-mean Fear of Failure, γ_{0022}				-8.69				6.18
Country-mean Occupational Aspiration, γ_{0023}				34.06				31.44
Country-mean Belief in the value of school, γ_{0024}				-38.00				-47.18
Country-mean Growth Mindset, γ_{0025}				27.98				26.37
School-level								
Rural, γ_{010}					-20.76***	-6.86*		-6.92*

City, γ_{020}	10.59**	5.32		5.30
Private School, γ_{030}	25.25***	2.77		2.83
Student-Teacher Ratio, γ_{040}	-3.19	10.82		10.59
Proportion of Fully Certified Teachers, γ_{050}	1.52	0.61		0.63
Class Size, γ_{060}	0.52**	0.21*		0.20
Extra-Curricular Activities in School, γ_{070}	9.05***	4.30**		4.27**
Student Behavior Hindering Learning, γ_{080}	-11.82***	-6.66***		-6.65***
Teacher Behavior Hindering Learning, γ_{090}	4.60**	2.44		2.43
School-mean Female, γ_{0100}		429.85		2.84
School-mean Parental Education Level, γ_{0110}		2.72		0.22
School-mean ICT Usage, γ_{0120}		0.23***		23.55***
School-mean Parents' Emotional Support, γ_{0130}		23.61***		18.43***
School-mean Sense of Belonging in School, γ_{0140}		18.44**		12.92**
School-mean Resilience Self-efficacy, γ_{0150}		13.02		-4.03
School-mean Mastery Goal Orientation, γ_{0160}		-4.06		1.81
School-mean Fear of Failure, γ_{0170}		1.81		7.90
School-mean Occupational Aspiration, γ_{0180}		7.95***		24.11***
School-mean Belief in the value of school, γ_{0190}		24.15		9.19
School-mean Growth Mindset, γ_{0200}		9.28***		23.37***
Student-level				
Female, γ_{100}			-8.70***	-8.69**
Parental Education Level, γ_{200}			-0.12	-0.12
ICT Usage, γ_{300}			5.49***	5.49***
Parents' Emotional Support, γ_{400}			3.86***	3.86***
Sense of Belonging in School, γ_{500}			1.26	1.26
Resilience Self-efficacy, γ_{600}			2.45**	2.45**
Mastery Goal Orientation, γ_{700}			1.32	1.32
Fear of Failure, γ_{800}			1.86	1.86
Occupational Aspiration, γ_{900}			8.81***	8.81***
Belief in the value of school, γ_{1000}			1.23	1.23
Growth Mindset, γ_{1100}			8.15***	8.15***

Note. *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$

Table 4. 5. *Proportion of Variance Explained*

Model	Country-level Variance		School-level Variance		Student-level Variance	
	Intercept Variance	R^2	Intercept Variance	R^2	Intercept Variance	R^2
Model 1	3382.67***	(Base)	2916.65***	(Base)	4506.93***	(Base)
Model 2-A	1602.27	0.5263	2916.65	0.0000	4506.93	0.0000
Model 2-B	437.28	0.8707	2916.29	0.0000	4506.94	0.0000
Model 2-C	231.71	0.9315	2916.22	0.0001	4506.94	0.0000
Model 3-A	3230.66	0.0449	2246.83	0.0001	4507.66	0.0000
Model 3-B	2884.29	0.1473	1432.52	0.2297	4512.45	-0.0002
Model 4	3381.16	0.0004	2931.24	0.5088	4310.47	-0.0012
Model 5	233.93	0.9308	1449.47	0.5030	4315.68	0.0444

Table 4. 6. *Half and Completely Standardized Regression Coefficients of Model 5*

Predictor	Raw Coefficient (γ)	$SD_{\bar{X}_{..k}}$	$SD_{\beta_{0j}} = \sqrt{\hat{\tau}_{\beta,00}}$	Half-standardized coefficient $\beta^* = \gamma(SD_{\bar{X}_{..k}})$	Completely standardized coefficient $\beta^{**} = \gamma(SD_{\bar{X}_{..k}}/\sqrt{\hat{\tau}_{\beta,00}})$
Level-3 Predictor ($\bar{X}_{..k}$)					
OECD (γ_{001})	18.02	0.50	58.16	9.01	0.15
STRICT (γ_{002})	25.89*	0.31	58.16	8.03	0.14
GDP (γ_{003})	1.01	2.10	58.16	2.12	0.04
GG (γ_{004})	153.97	0.05	58.16	7.70	0.13
GINI (γ_{005})	68.30	0.07	58.16	4.78	0.08
YRURAL (γ_{006})	92.12	0.17	58.16	15.66	0.27
YCITY (γ_{007})	94.02*	0.19	58.16	17.86	0.31
YPRIV (γ_{008})	33.15	0.20	58.16	6.63	0.11
YSTR (γ_{009})	-366.06**	0.04	58.16	-14.64	-0.25
YPRFT (γ_{0010})	56.67*	0.17	58.16	9.63	0.17
YCSIZE (γ_{0011})	-0.20	5.07	58.16	-1.01	-0.02
YCREA (γ_{0012})	-13.93	0.44	58.16	-6.13	-0.11
YSBHL (γ_{0013})	24.42	0.47	58.16	11.48	0.20
YTBHL (γ_{0014})	36.61***	0.45	58.16	16.47	0.28
YFEM (γ_{0015})	-263.69	0.02	58.16	-5.27	-0.09
YPARED (γ_{0016})	-14.45**	1.18	58.16	-17.05	-0.29
YICT (γ_{0017})	35.44**	0.63	58.16	22.33	0.38
YPARES (γ_{0018})	5.35	0.16	58.16	0.86	0.01
YBELN (γ_{0019})	48.37	0.19	58.16	9.19	0.16
YRSELF (γ_{0020})	-105.90**	0.22	58.16	-23.30	-0.40
YMAG (γ_{0021})	24.23	0.28	58.16	6.78	0.12
YFFAIL (γ_{0022})	6.18	0.23	58.16	1.42	0.02
YOA (γ_{0023})	31.44	0.27	58.16	8.49	0.15
YVSCH (γ_{0024})	-47.18	0.21	58.16	-9.91	-0.17
YGM (γ_{0025})	26.37	0.22	58.16	5.80	0.10

Level-2 Predictor ($\bar{X}_{\cdot jk}$)	Raw Coefficient (β)	$SD_{\bar{X}_{\cdot jk}}$	$SD_{\pi_{jk}} = \sqrt{\hat{\tau}_{\pi,00}}$	Half-standardized coefficient $\beta^* = \beta(SD_{\bar{X}_{\cdot jk}})$	Completely standardized coefficient $\beta^{**} = \beta(SD_{\bar{X}_{\cdot jk}}/\sqrt{\hat{\tau}_{\pi,00}})$
RURAL (γ_{010})	-6.90*	0.47	54.01	-3.27	-0.06
CITY (γ_{020})	5.30	0.49	54.01	2.59	0.05
PRIV (γ_{030})	2.83	0.40	54.01	1.12	0.02
STR (γ_{040})	10.59	0.83	54.01	0.88	0.02
PROFT (γ_{050})	0.63	0.34	54.01	0.21	0.00
CSIZE (γ_{060})	0.2*	10.45	54.01	2.09	0.04
CREA (γ_{070})	4.27**	1.03	54.01	4.42	0.08
SBHL (γ_{080})	-6.65***	1.26	54.01	-8.40	-0.16
TBHL (γ_{090})	2.43	1.16	54.01	2.83	0.05
XFEM (γ_{0100})	2.84	0.22	54.01	0.64	0.01
XPARED (γ_{0110})	0.22	1.79	54.01	0.39	0.01
XICT (γ_{0120})	23.55***	0.81	54.01	19.10	0.35
XPARES (γ_{0130})	18.43***	0.39	54.01	7.15	0.13
XBELN (γ_{0140})	12.92*	0.38	54.01	4.96	0.09
XRSELF (γ_{0150})	-4.03	0.39	54.01	-1.55	-0.03
XMAG (γ_{0160})	1.81	0.46	54.01	0.83	0.02
XFFAIL (γ_{0170})	7.9	0.36	54.01	2.82	0.05
XOA (γ_{0180})	24.11***	0.60	54.01	14.38	0.27
XVSCH (γ_{0190})	9.19	0.34	54.01	3.16	0.06
XGM (γ_{0200})	23.37***	0.39	54.01	9.13	0.17
Level-1 Predictor ($\bar{X}_{ijk}$)	Raw Coefficient (π)	$SD_{\bar{X}_{ijk}}$	SD_Y	Half-standardized coefficient $\beta^* = \pi(SD_{X_{ijk}})$	Completely standardized coefficient $\beta^{**} = \pi(SD_{X_{ijk}}/SD_Y)$
FEM (γ_{100})	-8.69**	0.50	105.28	-4.35	-0.04
PARED (γ_{200})	-0.12	3.10	105.28	-0.37	0.00
ICT (γ_{300})	5.49***	1.16	105.28	6.35	0.06
PARES (γ_{400})	3.86***	0.94	105.28	3.62	0.03
BELN (γ_{500})	1.26	0.94	105.28	1.18	0.01
RSELF (γ_{600})	2.45*	0.99	105.28	2.42	0.02
MAG (γ_{700})	1.32	1.01	105.28	1.33	0.01
FFAIL (γ_{800})	1.86	0.95	105.28	1.77	0.02
OA (γ_{900})	8.81***	1.00	105.28	8.81	0.08
VSCH (γ_{1000})	1.23	0.98	105.28	1.21	0.01
GM (γ_{1100})	8.15***	1.00	105.28	8.15	0.08

*Note. *p≤ 0.05; **p≤ 0.01; ***p≤ 0.001*

$SD_{\beta_{oj}}$ indicates the standard deviation of the Level-3 (γ_{000}) in the unconditional multilevel model (Model 1) and it was obtained as the square root of the estimate of the Level-3 variance and $SD_{\pi_{jk}}$ indicates the standard deviation of the Level-2 (β_{00k}) *in the unconditional multilevel model (Model 1) and it was obtained as the square root of the estimate of the Level-2 variance.*

Chapter 5: Discussion and Conclusion

In this study, hierarchical linear modeling (HLM) was conducted on the OECD Programme for International Student Assessment (PISA) dataset to estimate the magnitude of predictors' effects on mathematics achievement across countries. The PISA 2018 datasets collected 15 years old students in 7th grade and above across 58 countries were analyzed in the study. Since one of the significant purposes of this study was to examine the effects of the national and cultural contexts on math achievement, compositional variables were generated by aggregating student- and school-level variables. Then, country-, school-, and student-level predictors were added to the models to examine the nature and magnitude of student-level, school-level, and country-level factors. Chapter 5 presents summaries of the answer to research questions, discussions of the findings, implications, limitations and future directions of the study.

Answer to Research Questions

Research Question 1. Is there significant variability in mathematics achievement across countries? If so, how will total variation be allocated to student-, school-, and country-level?

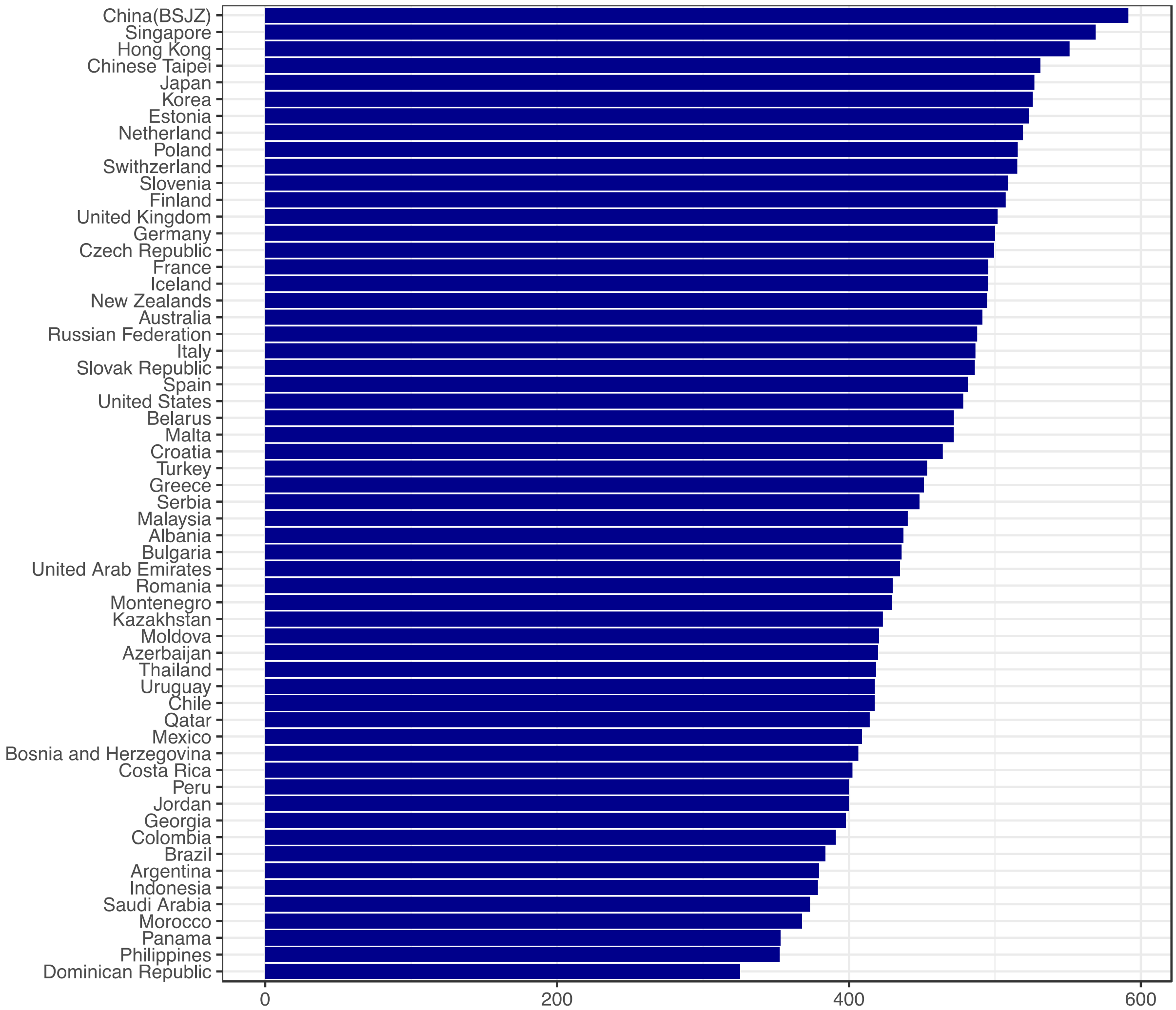
PISA 2018 included 79 countries, but 21 countries were excluded in this study. Plausible values that were obtained from the student posterior distribution were used to examine students' mathematics achievement. Table 5.1 shows students' weighted mathematics achievement score of 58 countries that were computed based on the average of 10 country-mean plausible values Figure 5.1 is a histogram represents the distribution of national math achievement in descending order. As shown in Figure 5.1, Dominican Republic had the score in mathematics, with a score of 325.1 and China (B-S-J-Z) had the highest score in mathematics, with a score 591.39 in PISA 2018. Countries and economies score in top 25% (499.61) in mathematics include China (B-S-J-

Z), Singapore, Hong Kong, Chinese Taipei, Japan, Korea, Estonia, Netherland, Poland, Switzerland, Slovenia, Finland, United Kingdom, and Germany indicating that East Asian countries have dominated the top PISA 2018 in mathematics achievement.

Table 5. 1. *International Mathematics Achievement Comparison*

Country	PM	Country	PM
Albania	437.22	Malaysia	440.21
Baku (Azerbaijan)	419.64	Malta	471.73
Argentina	379.45	Mexico	408.8
Australia	491.36	Moldova	420.6
Bosnia and Herzegovina	406.38	Montenegro	429.61
Brazil	383.57	Morocco	367.73
Bulgaria	436.04	Netherlands	519.23
Belarus	471.86	New Zealand	494.49
Chile	417.41	Panama	352.84
Chinese Taipei	531.15	Peru	399.84
Colombia	390.93	Philippines	352.57
Costa Rica	402.33	Poland	515.65
Croatia	464.21	Qatar	414.23
Czech Republic	499.47	Romania	429.92
Dominican Republic	325.1	Russian Federation	487.79
Estonia	523.42	Saudi Arabia	373.24
Finland	507.3	Serbia	448.28
France	495.41	Singapore	569.01
Georgia	397.59	Slovak Republic	486.16
Germany	500.04	Slovenia	508.9
Greece	451.37	Spain	481.39
Hong Kong	551.15	Switzerland	515.31
Iceland	495.19	Thailand	418.56
Indonesia	378.67	United Arab Emirates	434.95
Italy	486.59	Turkey	453.51
Japan	526.97	United Kingdom	501.77
Kazakhstan	423.15	United States	478.24
Jordan	399.76	Uruguay	417.66
Korea	525.93	B-S-J-Z (China)	591.39

Figure 5. 1. *Histogram of Mathematics Achievement of PISA 2018*



In response to the first research question, the fully unconditional model was conducted. This model found that 41.71% of the total variation was allocated to student-level, 26.99% of the total variation was allocated to school-level, and 31.30% of the total variation was allocated to country-level in mathematics achievement. There was significant large variability in school-level and country-level since the sum of variability at school- and country-level is mor than 50%. This indicates that examining school and country contexts should be needed.

Research Question 2. How are country-level variables associated with the country-mean student's mathematics achievement? Do the type of country's university admission procedure and country's culture of mindsets about intelligence significantly predict the country-mean student mathematics achievement?

In response to the second research question, Model 2-A, 2-B, and 2-C were constructed after completing the fully unconditional model. The pure country-level predictors excluding compositional variables that were created by aggregating lower-level predictors were added in Model 2-A. Then, school-level and student-level compositional variables were added gradually in Model 2-B and 2-C to examine any difference in effects of country-level predictors after controlling for school-level compositional variables which can represent characters of a country.

In Model 2-A, it was found that there were three variables associated with the country-mean student's mathematics achievement: Strict university admission system (STRICT), GDP per capita (GDP), and GINI index. In Model 2-B, OECD country (OECD), country-mean student-teacher ratio (YSTR), country-mean proportion of fully certified teachers (YPFCT), country-mean extra-curricular activities in school (YCREA), and country-mean student behavior hindering learning (YSBHL) were statistically significantly associated with the country-mean math achievement. At the country-level, based on Model 2-C, there were four variables that had a statistically significant positive association with country-mean student's mathematics achievement. strict university admission system (STRICT), country-mean student behavior hindering learning (YSBHL), country-mean teacher behavior hindering learning (YTBHL), and country-mean ICT usage (YICT) had a statistically significant positive association with student's mathematics achievement while country-mean student-teacher ratio (YSTR), country-mean parental education level (YPARED), and country-mean resilience self-efficacy (YRSELF) had a statistically significant negative association after controlling other predictors in this model. Accordingly, country's university admission procedure could predict the country-mean student's mathematics achievement while the country's culture of mindsets about intelligence could not. Accordingly, the study fails to confirm the hypothesized relationship between country-mean growth mindset and country-mean student's mathematics achievement.

Research Question 3. How are school-level variables associated with school-mean student mathematics achievement? Do extra-curricular activities in schools significantly predict the school-mean student mathematics achievement?

In response to the third research question, Model-3A and 3-B were generated by adding school-level predictors in those models. Only pure school-level predictors were added in Model 3-A, then Model 3-B were developed by adding compositional variable to Model 3-A. In Model 3-A, school locale (RURAL & CITY), type of school (PRIV), Class size (CSIZE), extra-curricular activities in school (CREA), student behavior hindering learning (SBHL), and teacher behavior hindering learning (TBHL) were statistically significantly associated with the school-mean math achievement. Among those seven variables, the variable indicating school located in city (CITY), type of school (PRIV), student-teacher ratio (STR), Class size (CSIZE), extra-curricular activities in school (CREA), and teacher behavior hindering learning (TBHL) had a statistically significant positive association with school-mean math achievement while the variable indicating school located in rural area (RURAL) and student behavior hindering learning (SBHL) had a statistically significant negative association. In Model 3-B, there were some changes in association between predictors and the dependent variable. The variable indicating private school (PRIV) had no statistically significant association with school-mean math achievement after controlling for compositional variables. Among compositional variables, school-mean ICT usage (XICT), school-mean parents' emotional support (XPARES), school-mean sense of belonging in school (XBELN), school-mean occupational aspiration (XOA), and school-mean growth mindset (XGM) had a statistically significantly associated with the school-mean math achievement. Accordingly, extra-curricular activities in school significantly predict the school-mean student's mathematics achievement even after controlling for other school-level predictors.

Research Question 4. How are student-level variables associated with the student's mathematics achievement? Do student's ICT usage, growth mindset, and resilience self-efficacy significantly predict the student's mathematic achievement?

In response to the fourth research question, 11 student-level predictors were added in Model 4. From the results of Model 4, gender (FEM) had a negative association with student mathematics achievement, which means that male students scored higher than female students on math achievement. ICT usage (ICT), parents' emotional support (PAREA), mastery goal orientation (MAG), occupational aspiration (OA), and growth mindset (GM) had a statistically significant association with student's mathematics achievement. However, resilience self-efficacy had no statistically significant association with math achievement after controlling for other predictors in this model.

Research Question 5. Are there any school-level and country-level compositional factors strongly associated with mathematics achievement?

In response to the last research question, the final model (Model 5) was constructed by adding all predictors at each level. From results of Model 5, several compositional effects were detected for school- and country-level. Firstly, there was only one factor that compositional effects were detected from both school- and country-level, which was ICT usage. To be specific, there was a distinct effect of school-mean ICT usage (XICT) variable (Level 2) after accounting for the corresponding ICT usage (ICT) variable (Level 1). Also, there was a significant difference between country-mean ICT usage (YICT) variable (level 3) and ICT usage (ICT) variable (Level 1). Meanwhile, the following three variables that were showed school compositional effects on math achievement: parents' emotional support (PARES), occupational aspiration (OA), and growth mindset (GM). The compositional effects were detected because there were distinct divergences of the within- and between-school regression coefficients.

Discussion

Ono of the main purposes of this study was to explore the effects of the national and cultural contexts on students' mathematics achievement. Then, the nature and magnitude of country-level factors, as well as school- and student-level factors that are associated with math achievement was examined by using HLM analysis. This study used a three-level HLM and the HLM analyses showed that there are various predictors that were associated with students' math achievement at each level. In the discussion section, the summary of findings, implications, significance and limitations of this study, and directions for future research were discussed. From the summary of findings were described from country-level first and student-level because the predictors addition started at country-level and ended up with student-level in the models. Also, examining country-level predictors first is important because the current study is a cross-national comparison to examine contextual factors predicting math achievement.

Country-level (Level 3) predictors

According to the final model (Model 5) in this study (See Table 4.4), the strict university admission system, the country-mean city, country-mean proportion of fully certified teacher, country-mean teacher behavior hindering learning, and country-mean ICT usage were positively associated with math achievement while country-mean student-teacher ratio, country-mean parental education level, and country-mean resilience self-efficacy were negatively associated with math achievement. The results from the completely standardized regression coefficient shows (see Table 4.6) that the most important variables in predicting student's math achievement at country-level were the following order: country-mean resilience self-efficacy (-0.40), country-mean ICT usage (0.38), country-mean city (0.31), country-mean parental education level (-0.29), country-mean teacher behavior hindering learning (0.28), country-mean student-teacher ratio (-0.25), country-mean fully certified teachers in school (0.17), and the strict university admission system (0.14).

One of interesting findings from the final model was that the partial correlation between country-mean resilience self-efficacy and country-mean students' math achievement became negative after controlling for other predictors in the model which was opposite of the results of the correlation matrix among the student-level predictors with the dependent variable (See Table 4.2). Figure 5.2 shows the scatterplot show the marginal correlation between student's resilience self-efficacy and math achievement with regression lines based on 58 countries. As shown in the Figures, student's resilience self-efficacy and math achievement had a positive relationship. This indicates that students who believe more strongly in their ability to cope with difficult or challenging experience show higher math achievement. On the other hand, Figure 5.3 shows the scatterplot of country-mean resilience self-efficacy against country-mean math achievement. This figure does not indicate students with lower resilience self-efficacy show higher math achievement. Instead, shift of meaning plays a role in the macro-level relationship. The meaning of resilience self-efficacy variable that is aggregated to the country-level distinct from the meaning of student-level resilience self-efficacy. The occurrence of this counterintuitive association might be due to a shift of meaning. That is, if we make inferences about student's resilience self-efficacy based on country-mean resilience self-efficacy, an ecological fallacy (i.e., error in interpretations of the results) may occur by ignoring the disparity of the meaning between the country-level and student-level. The country-mean resilience self-efficacy refers to the cultural context of country because it is a country-level variable. In the other word, the country-mean resilience self-efficacy can be interpreted to mean beliefs and values that are shared among people in a country. As a validity of this interpretation, see Figure 5.5 below. As shown in Figure 5.5, East Asian countries generally show low country-mean resilience self-efficacy while those countries show high country-mean math achievement. This may represent the countries have a cultural characteristic that people tend to avoid failures and challenges and seek stability.

Figure 5. 2. Scatterplot-relationship between resilience self-efficacy (RSELF) and math achievement (PV1MATH)

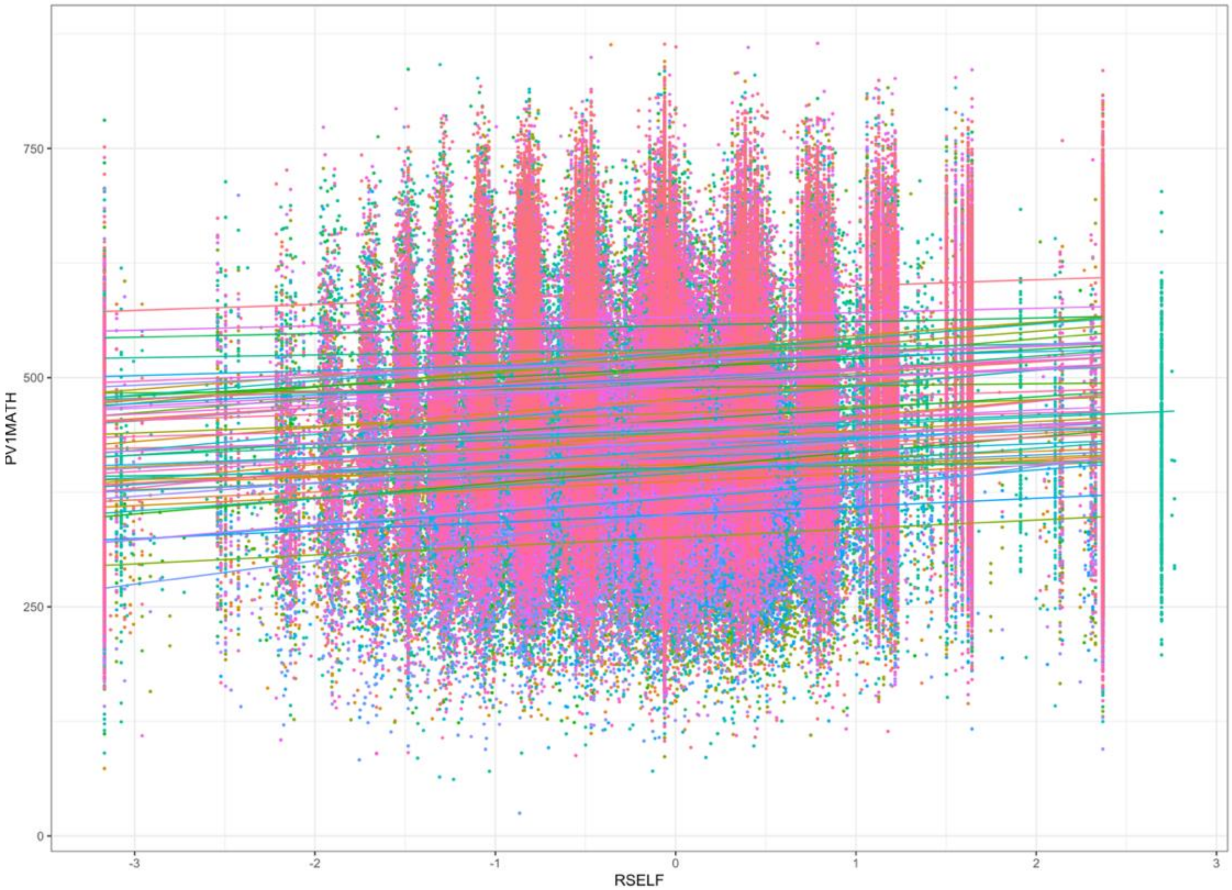
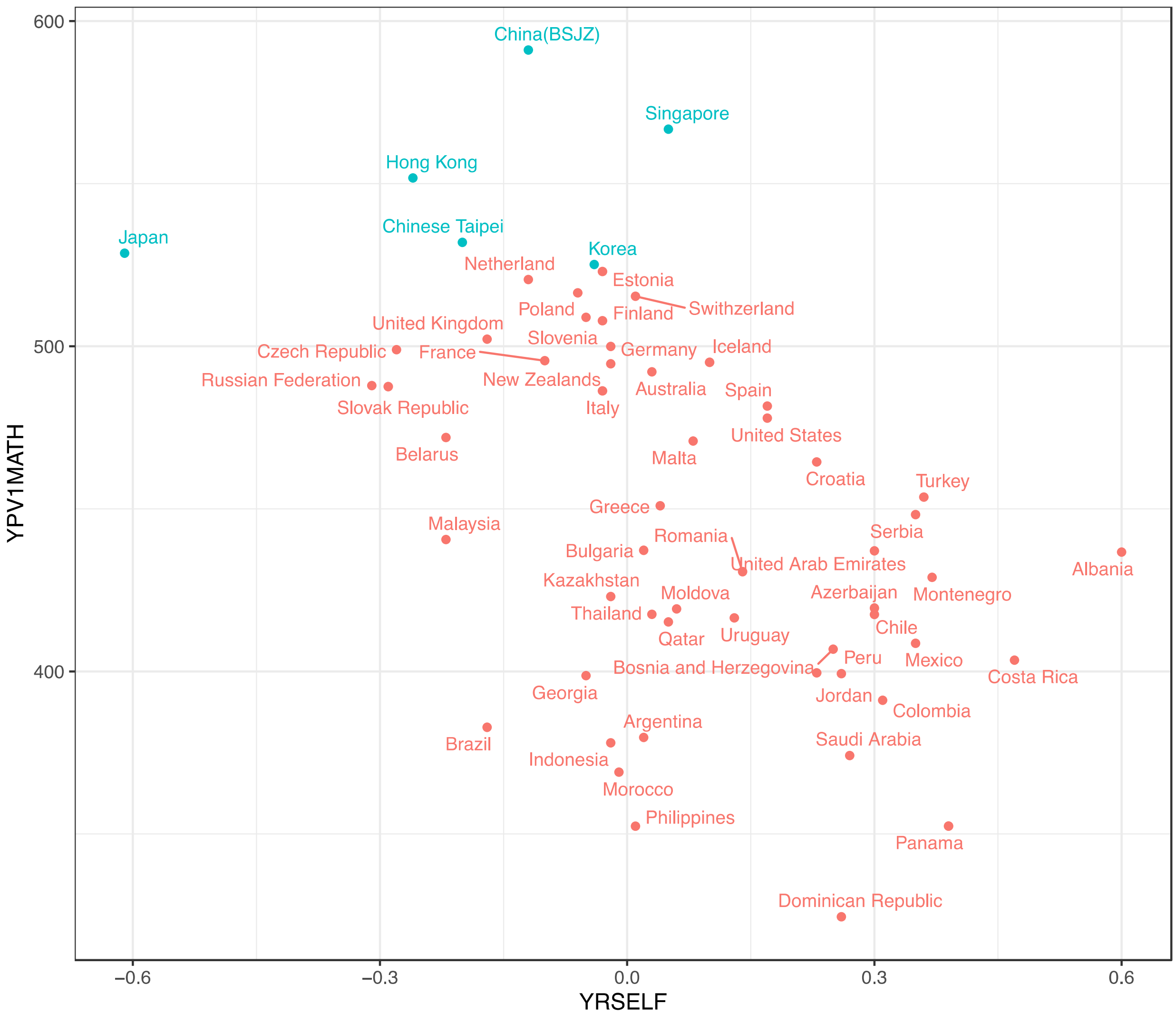


Figure 5. 3. Scatterplot-relationship between country-mean resilience self-efficacy (YRSELF) and country-mean math achievement (YPV1MATH) by grouping East Asian Countries and Not East Asian Countries



Second, the final model found that country-mean teacher behavior hindering learning which represents school climate in school-level predictors had positive association with students' math achievement after controlling for other predictors in the model. As shown in school-level correlation matrix from Table 4.2 from the previous chapter, there was a negative correlation between the school-level teacher behavior hindering learning variable and school-mean students' math achievement. Figure 5.4 shows the scatterplot displaying the relationship teacher behavior hindering learning variable and school-mean students' math achievement. Such counterintuitive association phenomena may be due to shift of meaning. It shows that meaning of a micro-level variable aggregated to the macro-level is distinct from the micro-level variable. To be specific, the teacher behavior hindering learning variable was collected in questionnaire distributed to school's principals. In PISA 2018, school principals were asked to complete the describe the extent to which they think that students' learning is hindered by teachers' behaviors. Therefore, the values of the variables reflect principal's subjective perceptions. The average of the school-level variables may be used as an index for countries' cultural climate; hence higher scores of the country-mean teacher behavior hindering learning from countries may represent greater level of standard for school climate. In other words, country-mean teacher behavior hindering learning may represent the level of standard for teacher in countries. Figure 5.5 shows the scatter plot regarding relationship between country-mean teacher behavior hindering learning and country-mean math achievement. As shown in the scatter plot, East Asian countries including China, Chinese Taipei, Hong Kong, Singapore, Japan, and Korea generally higher than other countries. This may indicate that East Asian countries have higher standard for teacher behaviors.

Figure 5. 4. Scatterplot-relationship between school-mean teacher behavior hindering learning and (XTBHL) school-mean math achievement (XPV1MATH) by grouping 58 countries

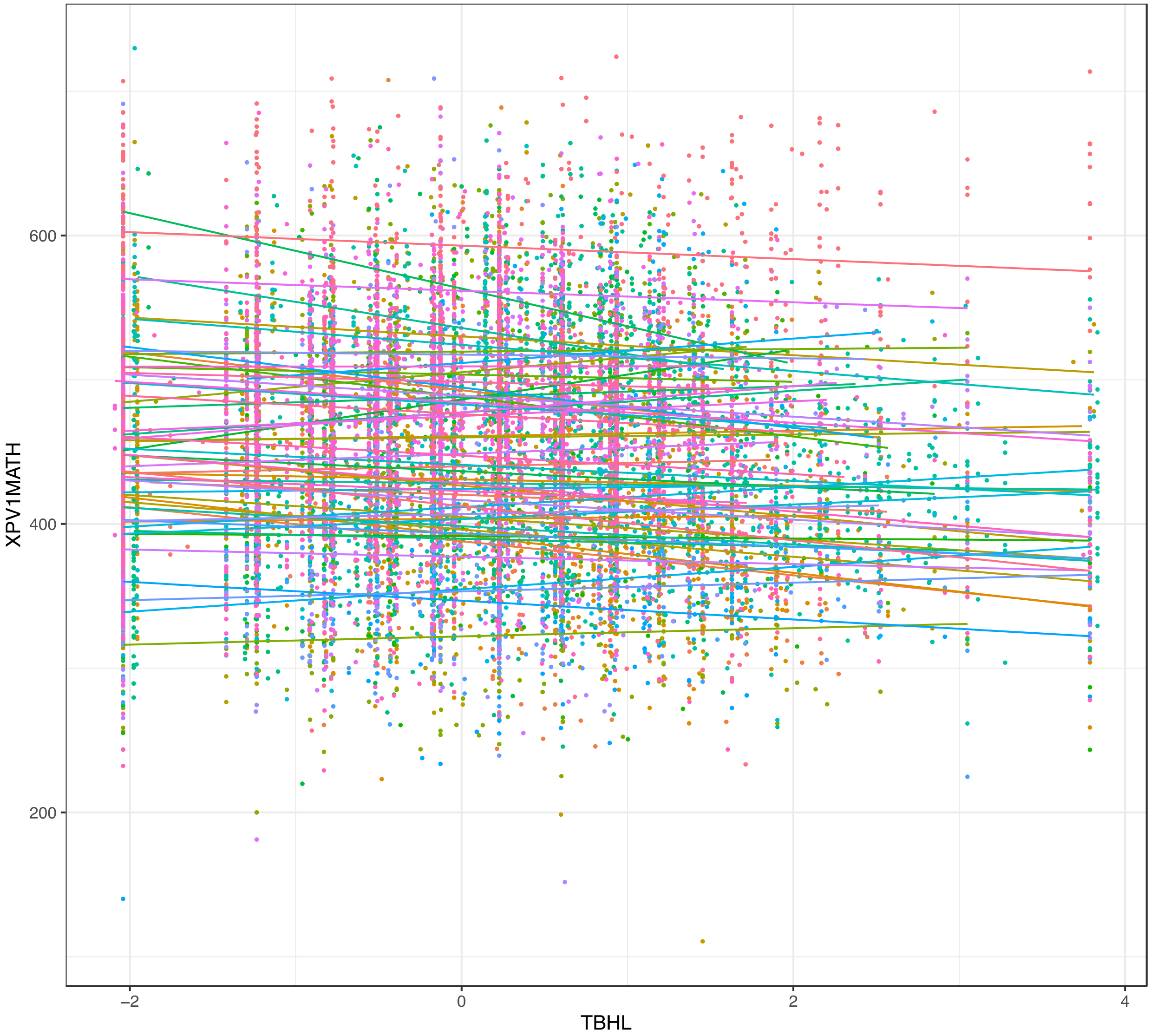
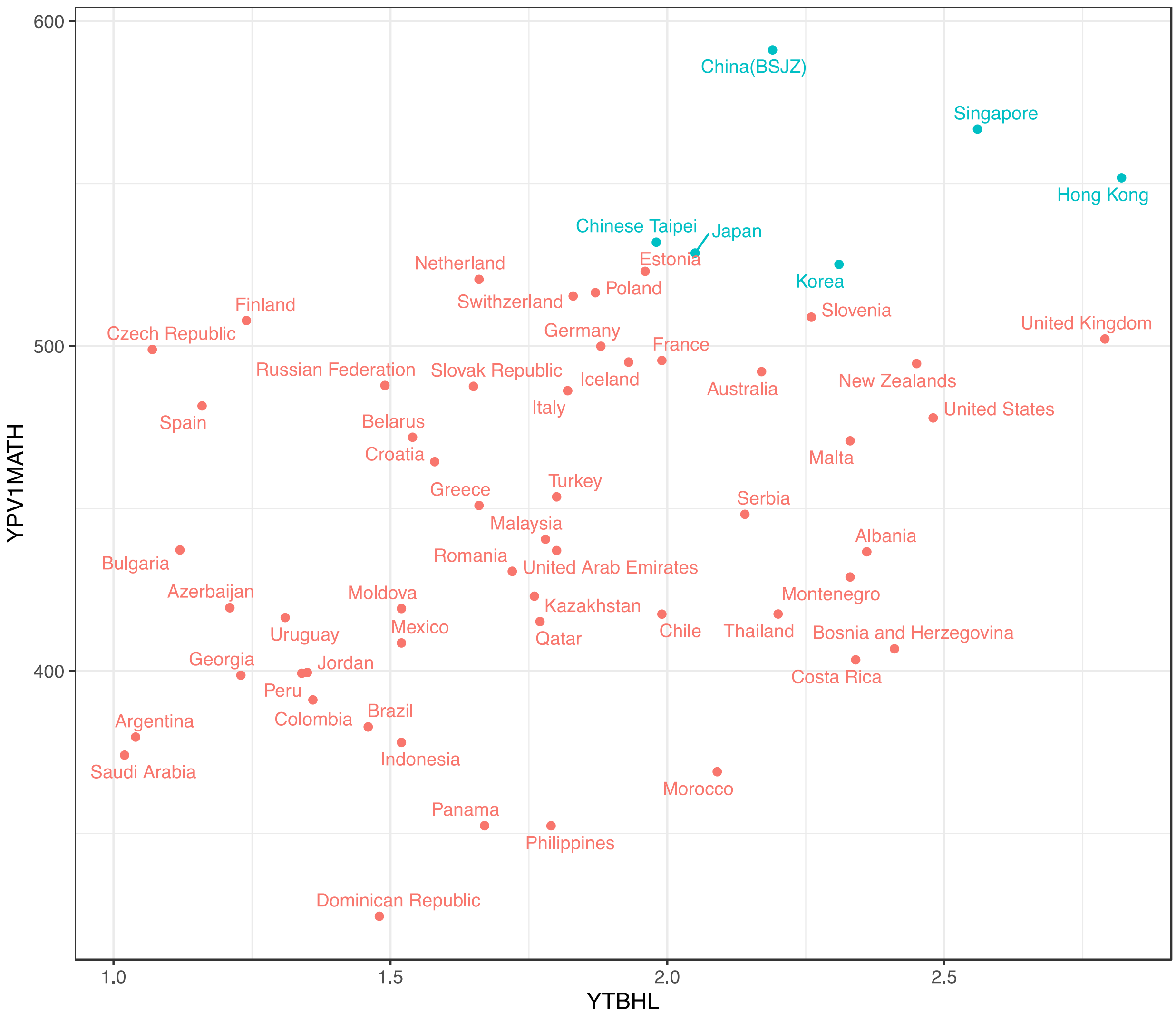


Figure 5. 5. Scatterplot-relationship between country-mean teacher behavior hindering learning (YTBHL) and country-mean math achievement (YPV1MATH) by grouping East Asian Countries and Not East Asian Countries



Third interesting finding was that the country-mean parental education level had a negative association with country-mean students' math achievement. This result was opposite to majority of previous literature that parents' education is positively associated with their children's academic outcomes. In order to find any significant predictor that changed the association, the study added each country-level predictor one by one to the model. Then, this study found that the coefficient for country-mean parental education level went from positive to negative when the country-mean ICT usage was added as the sole predictor. Scatterplots describing the relationship between country-mean parental education and country-mean math achievement were created to understand the results of the model. As shown in Figure 5.6, a group of countries have high level of country-mean ICT usage (larger than 50^{th} percentile) showed a negative relationship between country-mean parental education and country-mean math achievement while a group of countries have low level of country-mean ICT usage (smaller than 50^{th} percentile) showed a positive relationship between country-mean parental education and country-mean math achievement. In addition, another scatter plot was created for cross-national comparison. Figure 5.7 describes relationship between country-mean parental education and country-mean math achievement grouping by East Asian countries, developed Europe countries (selected by Developed Markets (DM) Index from Morgan Stanley Capital International (MSCI)), and other countries. The reason for grouping countries into three was to explore see differences in pattern of association between the two variables. As shown in the figure, a group of East Asian countries had a negative relationship between country-mean parental education and country-mean math achievement. On the other hand, a group of developed Europe countries showed almost zero correlation between those two variables. A group of other countries including United States showed a positive correlation between those two variables. This situation in which a relationship observed at the group reverse is known as Simpson’s paradox (Blyth, 1972). The results of the model found that country-mean ICT usage plays a role as a confounding variable which reversed the association between country-mean parental education and country-mean math achievement.

Figure 5. 6. Scatterplot-relationship between country-mean parental education level (YPARED) and country-mean math achievement (YPV1MATH) by grouping ICT usage

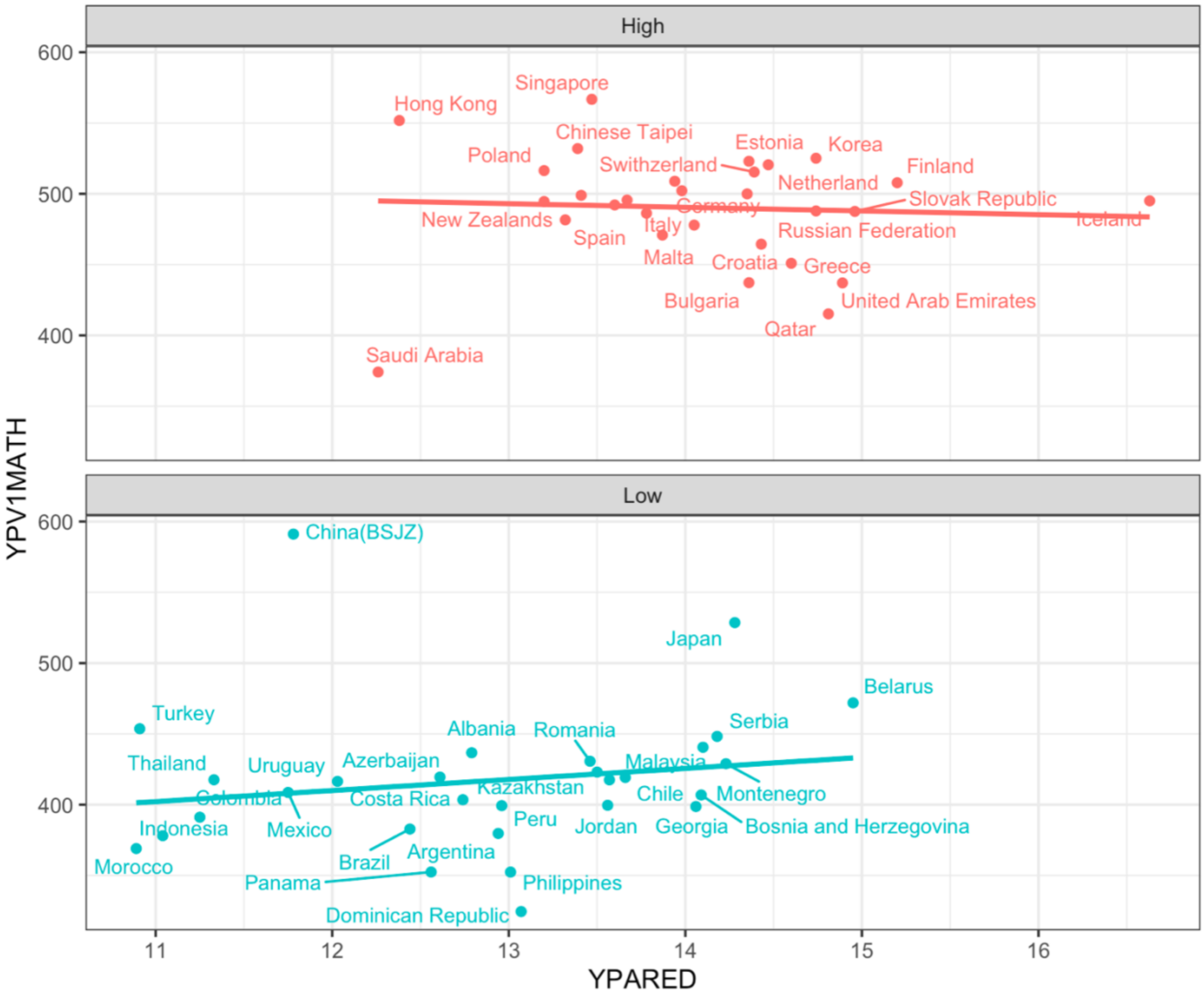
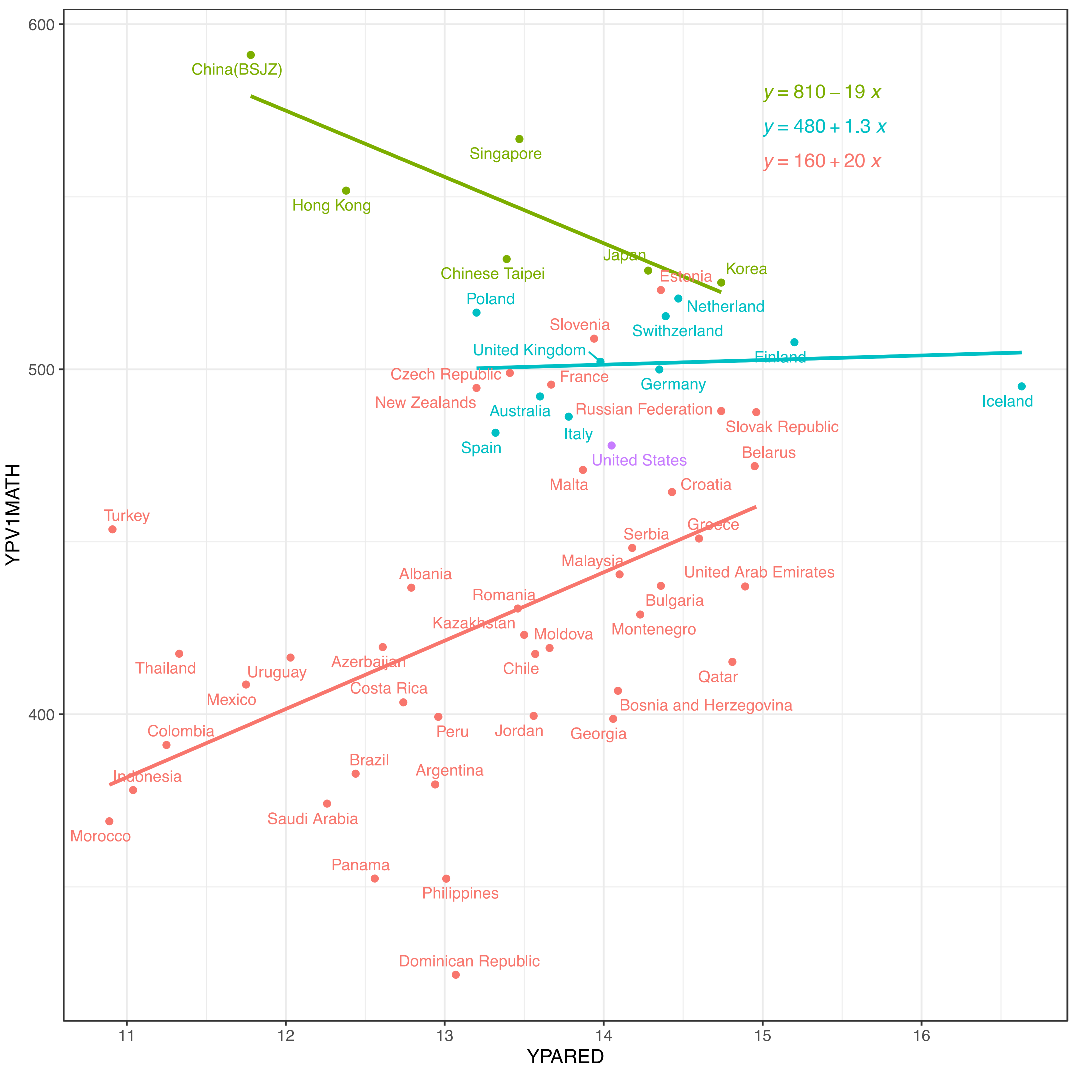
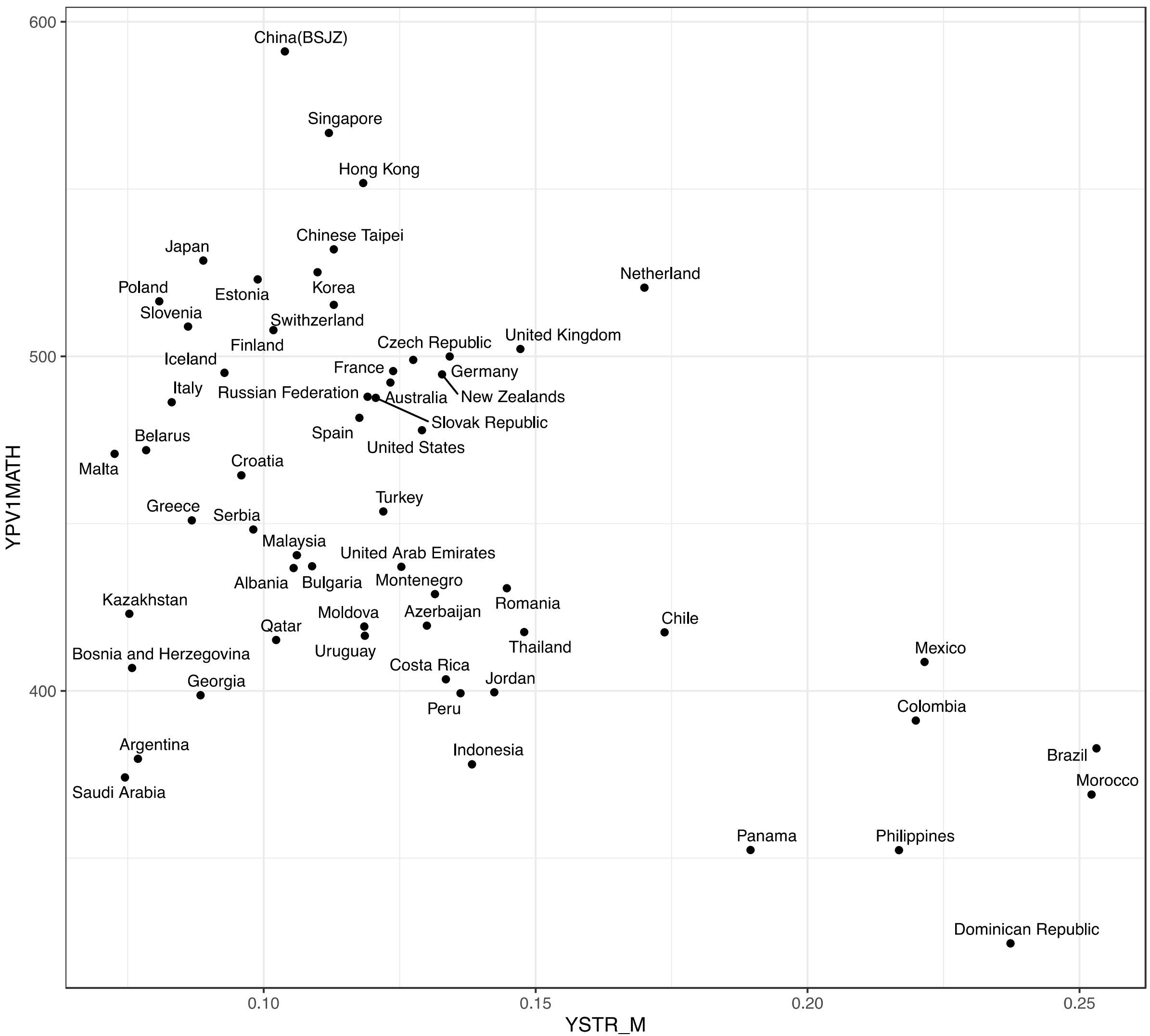


Figure 5. 7. Scatterplot-relationship between country-mean parental education and country-mean math achievement



Fourth, country-mean student-teacher ratio was negatively associated with country-mean math achievement. This means that countries have higher student-teacher ratio predict lower math achievement. Student-teacher ratio and class size are related, but distinct terms. Student-teacher ratio is calculated by dividing the number of students by the number of teachers in a school while class size is obtained by dividing the number of students by the number of classes. Therefore, student-teacher ratio indicates how many students a teacher can take care of their learning. The final model (Model 5) was found that country-mean student-teacher ratio is still strong predictor of country-mean math achievement even after controlling for other predictors in the model.

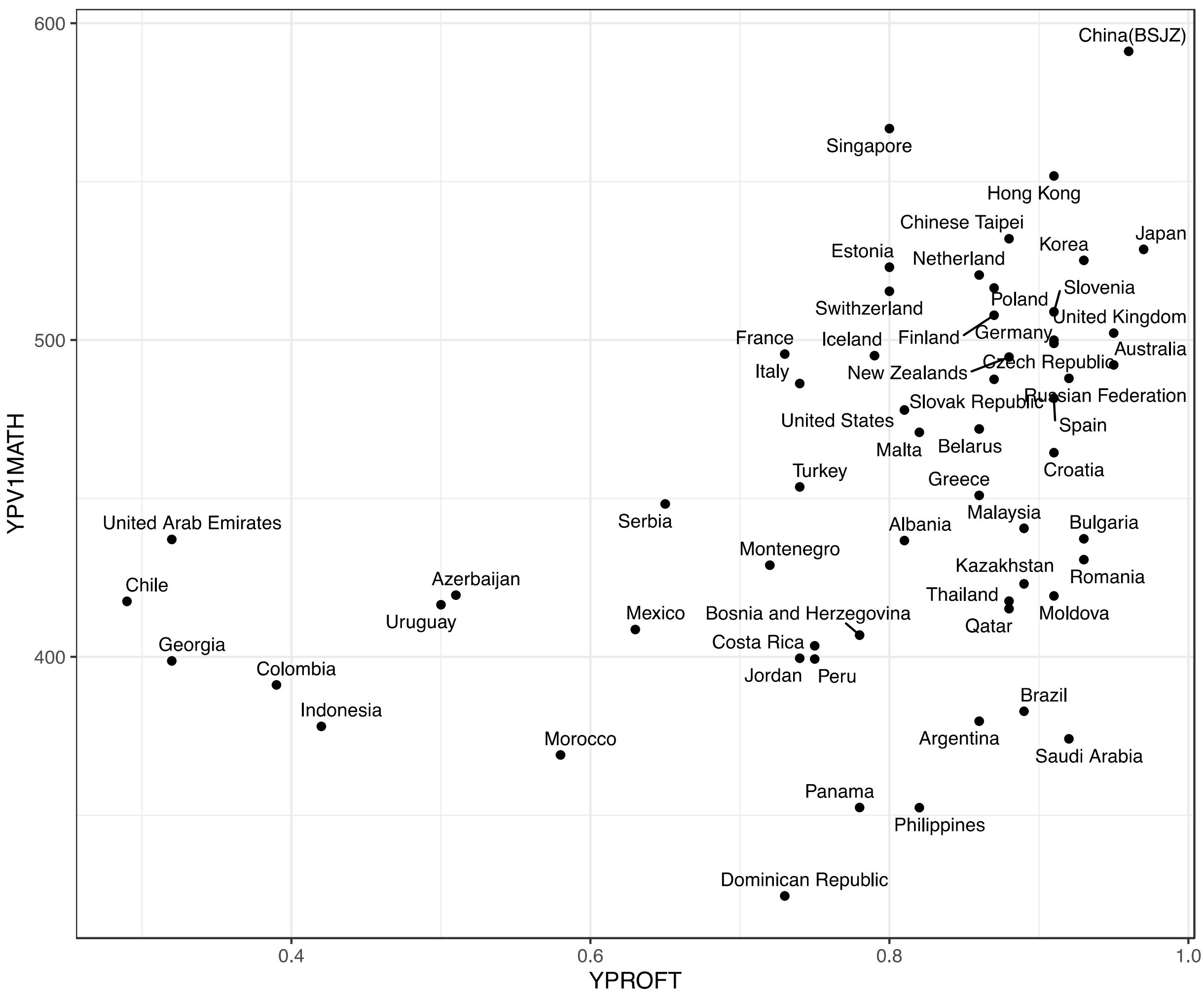
Figure 5. 8. Scatterplot-relationship between country-mean student-teacher ratio and country-mean math achievement



Lastly, country-mean proportion of fully certified teacher was positively associated with country-mean math achievement. This means that countries have higher percentage of fully certified teacher show higher country-mean math achievement after controlling for other predictors in the model. As shown in Figure 5.9, China has the highest percentage of fully certified teachers in school and shows highest country-mean math achievement. Other than

China, other East Asian countries or economies including Singapore, Hong Kong, Chinese Taipei, Korea, and Japan show relatively higher country-mean proportion of fully certified teachers in school than other countries. The result indicates that country-mean proportion of fully certified teachers may represent national characteristics of criteria for the teacher selection. Accordingly, countries maintain high standard for teacher employment show higher country-mean math achievement.

Figure 5. 9. Scatterplot-relationship between country-mean proportion of fully certified teachers and country-mean math achievement



School-level (Level 2) Predictors

Based on the final model (Model 5), several variables were found to be statistically significant at school-level. Class size, extra-curricular activities in school, school-mean ICT usage, school-mean parents' emotional support, school-mean sense of belonging in school, school-mean occupational aspiration, and school-mean growth mindset were positively associated with student's math achievement while rural and student behavior hindering learning were negatively associated with math achievement. The results from the completely standardized regression coefficient shows (see Table 4.6) that the most important variables in predicting student's math achievement at school-level were the following order: school-mean ICT usage (0.35), school-mean occupational aspiration (0.27), school-mean growth mindset (0.17), student behavior hindering learning (-0.16), school-mean parents' emotional support (0.13), school-mean sense of belonging in school (0.09), extra-curricular activities in school (0.08), rural (-0.06), and class size (0.04).

The final model found that schools in rural area show lower math achievement than school in city. This indicates schools in city perform better in schools in rural. Also, schools providing more extra-curricular activities show higher math achievement. This result could have some policy implication since creativity has not been considered as an important predictor in math achievement (Švecová et al., 2014). Even there was a previous study asserted that creativity and mathematics are negatively associated since it leads fixed mindset (Haase & Hanel, 2022). Accordingly, this finding can provide evidence that providing creative activities in schools is an effective way to improve mathematics achievement. The model also found that class size is positively associated with math achievement. This finding seems to contradict some other studies argued that the smaller class size is better in students' learning (Mosteller, 1995; Jepsen &

Rivkin, 2009). Accordingly, increasing budget to reduce average class size might not a prudent investment. Moreover, school-mean parents' emotional support, school-mean sense of belonging in school, school-mean occupational aspiration, and school-mean growth mindset predict higher math achievement. These results indicate that individuals' psychological factors may affect the groups they belong.

Student-level (Level 1) Predictors

From the final Model (Model 5), it was found that five variables including gender, ICT usage, parents' emotional support, mastery goal orientation, occupational aspiration, and growth mindset significantly predict math achievement. Among those significant predictors, the variable indicating female had a negative association with math achievement even after controlling for other predictors in the model. The results from the completely standardized regression coefficient shows (see Table 4.6) that the most important variables in predicting student's math achievement at student-level were the following order: Occupational Aspiration (0.08), growth mindset (0.08), ICT usage (0.06), female (-0.04), parents' emotional support (0.03), and resilience self-efficacy (0.02).

As mentioned in several studies in the chapter 2, this model found that males and females differ in mathematics achievement. Using more ICT resources was positively associated with math achievement which consists with previous literature. Among variables representing parents' characteristics, only parents' emotional support was positively associated with math achievement which was inconsistent with previous studies that parental education level is a significant predictor of students' academic outcome. This model found that emotional support is more important than academic backgrounds of parents. Also, mastery goal orientation, occupational aspiration, and growth mindset are significant predictors of math achievement among non-cognitive abilities. The results help explain findings from previous literature that non-cognitive abilities effect on academic performance.

Compositional Effects

This study investigated compositional effects on students' math achievement by adding all variables at each level in the final model (Model 5). The logic of compositional effects begin with the assumption individual-level outcomes are influenced by not only individual characteristics but also by characteristics of the higher-level units or context. To be specific, the study assumed that characteristics of students within different schools and within different countries predict different math achievement.

The most interesting finding in the model was that the positive compositional effect of ICT usage explained significant amount of between schools and countries variance even after controlling for other predictors in the final model. The results indicate that a student attends a school where the school average of students' ICT usage is high may perform better in math achievement. Also, a student in a country where the average ICT usage of students is high may perform better in math achievement. The effect of the country's ICT usage composition was stronger than country's ICT usage composition. The expected change in mathematics score for a one-unit change in country-mean ICT usage is 29.95 while expected change in mathematics score for a one-unit change in school-mean ICT usage is 18.06. This strong school and country contextual effect of ICT usage on math achievement can be the demonstrate that Internet and Internet devices need to be effectively integrated to learning mathematics.

There are three statistically significant compositional variables at school-level. In other words, the effect on students' math achievement associated with three characteristics of the school including school-mean parents' emotional support, school-mean occupational aspiration, and school-mean growth mindset. First, the finding of parents' emotional support positive compositional effect indicates that students in school with higher school-mean parents' emotional support are more likely to perform better in math achievement even after controlling for the student-level predictors in the model. This finding demonstrates that the influence of individual student's family atmosphere extends beyond the student's own families to the schools the students attend. Also, the model in this study confirms the literature that peer compositional effects play an important role in improving students' academic outcome. The model found that school composition effects based on their non-cognitive abilities (growth mindset and occupational aspiration) are important in predicting students' math achievement positively even after controlling for other predictors at each level. The results indicate that students may influenced by their peers' attitude and motivation. The expected change in a mathematics score for a one-unit change in school-mean occupational aspiration is 15.30 and the expected change in a mathematics score for a one-unit change in school-mean growth mindset is 15.22. The results indicate that students attend schools with greater percentage of students expressing a more career-related goal and believing their abilities can be developed through their efforts are likely to perform better in math achievement.

Implications

The findings of the study provide important practical and theoretical implications for policy makers, educator, and researchers. First, the findings supported the hypothesis of this study that mathematics achievement was associated with national and cultural contexts because the study found 31.30% of the total variation was accounted for country level in math achievement. This result provided a justification that country characteristics should be examined in a context of cross-national comparison study. The findings were also consistent with the hypothesis of this study that country characteristics were associated with student's math achievement that was underpinned by Vygotsky's sociocultural theory that social and cultural interaction are essential to learning and Bandura's social cognitive theory that learning occurs through social interaction.

Secondly, the current study supported a hypothesis that the type of university admission procedure as a national policy significantly predicts the country-mean student's mathematics achievement. The result indicated that countries which require stricter procedures to apply universities were more likely to show higher math achievement. The finding is unique in that it tried to examine the effect of a university entrance system on math achievement by using a multilevel analysis. Also, the finding supported early research showing that types of university admission procedure were associated with students' competition for entering university and it can lead to higher academic achieving (Lee, 2018). Moreover, the results provide essential knowledge for education policymakers and university stakeholders to make more effective strategies for college admission decisions.

Third, one of the unique findings of the present study was that the shift of meaning played important roles in interpreting the country-mean proportion of fully certified teachers and country-mean teacher behavior hindering learning in the final model. The meanings of two variables were apparently distinct from the meanings as school-level variables. The country-mean proportion of fully certified teachers and country-mean teacher behavior hindering learning can be used as indices for 'national standard for teacher', which seemed to provide a reasonable explanation of the results we obtained. As shown in Figure 5.3 and 5.9, higher values in country-mean proportion of fully certified teachers and country-mean teacher behavior hindering learning indicated higher level of standard for teacher and those two are positively associated with country-mean achievement. To be specific, the country-mean teacher behavior hindering learning may represent a country's professional culture of teachers. Accordingly, the higher country average value of school principal's perspective that teachers' unprofessional behaviors are more likely to harm students' learning indicates higher country's standard for teacher behavior. In addition, the country-mean proportion of fully certified teachers may indicate a country's standard for teacher selection. The higher country average value of proportion of fully certified teachers indicated that the country required higher criteria for hiring teachers. In terms of implications, investing in increasing the national average of teacher qualification standard should be regarded to promote student's math achievement. As shown in Figure 5.3 and 5.9, East Asian countries including China, Chinese Taipei, Hong Kong, Japan, Korea, and Singapore generally showed high values in the country-mean teacher behavior hindering learning and proportion of fully certified teachers. Also, those countries were ranked in the top 5 in mathematics achievement (See Figure 5.1). Since those five East Asian countries share Confucian heritage cultures (CHC), the finding in this study supported previous research that teachers in countries sharing CHC place emphasis on students' academic success (Sollenberger, 1968; Kim & Park, 2000). In addition, the counterintuitive association occured in the relationship between country-mean resilience self-efficacy and country-mean math achievement. The shift of meaning seemed to have played a role here, too. The country-mean resilience self-efficacy might indicate beliefs and values that were shared among people in a country. As mentioned above, East Asian countries generally show lowed country-mean resilience self-efficacy, and the results may represent the countries have a cultural characteristic that people tend to avoid challenges and failures. This tendency of avoiding failure might be because those countries have more competitive educational settings than other countries. As mentioned earlier, secondary schools in

Japan and Korea focus entirely on test preparation for college prep and this leads competitive educational settings. One of reasons for competition for entering elite universities is due to elitism based on the tradition of Confucian driven education. Given intensely competitive educational settings, students in those countries may be associated with low resilience self-efficacy.

The fourth finding was that ICT usage was an important predictor at each level in the study. The study found that the country-mean ICT usage played a role as a confounding variable which reversed the sign of the correlation between the country-mean parental education level and country-mean math achievement. In the final model, there was a negative association between those two variables which was not consistent with previous research that parental education level and their children academic performance was positively associated. The study found that the negative association between a pair of variables was due to the country-mean ICT usage, which was the responsible variable that changed the sign of the association. As shown in Figure 5.6, the relationship between the country-mean parental education level and country-mean math achievement was negative in countries with high country-mean ICT usage while the relationship between the country-mean parental education level and country-mean math achievement was positive in countries with low country-mean ICT usage. Moreover, the compositional effect was detected for the ICT usage at school- and country-level. The finding indicates that the school-mean ICT usage and country-mean ICT usage promote student's math achievement even after controlling for student-level predictors. This finding provided strong evidence in supporting previous research that ICT plays an important role in student's academic achievement (Escueta et al., 2017; Ishaq et al., 2020; Suleman et al., 2016). Accordingly, the finding provided practical implication for educators and policy makers that supporting ICT resources and providing good learning environment through ICT to students would facilitate student's mathematics achievement. The study confirmed that the rapid development of ICT over the past decades had led not only nation's economic development but also student's mathematics achievement. Therefore, optimizing ICT infrastructure should be needed to for high and sustainable students' math achievement.

Also, the study found that extra-curricular activities in school was positively associated with math achievement. The results match with those of Long (2015) who examined the association between extra-curricular activities and socioeconomic outcomes in respondents' lives such as post-secondary education, full-time employment status, and income using two different U.S. nationally representative data, i.e., NELS88 and ELS02, for high school students collected in different decades. He found that there were statistically significant and substantively meaningful positive associations, and they were consistent across two decades of U.S. high school students' data. But to the best of my knowledge, there was no study that examined the association using students from many nations. This finding leads to implication for researchers that student's math achievement can be improved by providing extra-curricular activities in schools. Since few studies except Long (2015) have examined the relationship between extra-curricular activities in school and math achievement, this finding supports the assertion that researchers need to investigate the relationship between extra-curricular activities in school and math achievement. In addition, the finding provides evidence to educators and policy makers to invest a wide variety of extra-curricular activities in school for improving student's math achievement.

Lastly, the results of the study showed that mastery goal orientation, occupational aspiration, and growth mindset were significant predictors of math achievement among non-cognitive abilities. The findings are consistent with previous research that non-cognitive factors played an important role in academic outcomes. These findings also have practical implications for teachers and education policy makers. First, teachers need to understand the importance of non-cognitive abilities and build strategies to foster them in school. In addition, policymakers should not overlook their importance and provide resources and education policies to contribute development of non-cognitive skills.

Limitations and Future Research Direction

Despite some important contributions of the study, there are some limitations in the study. First, the current research was cross-national study conducted by using PISA 2018 cross-national dataset that was administrated to 15 years old (seventh grade and above) students around 79 countries. However, the current study only analyzed dataset of 58 countries since the PISA 2018 had missing data for many countries at the school-level. For example, the study was not able to add the variable about the proportion of teachers with master's degree at the school-level which is an important variable for measuring teacher quality. This is because Japan, one of major countries for the study, did not respond to the questionnaire about the proportion of teachers with master's degree in school. In addition, several countries did not respond to the class size and student-teacher ratio questionnaire. Moreover, there was no data on GINI Index or Gender Gap Index for several countries including Brunei Darussalam, Kosovo. Therefore, dataset for those countries were not added to the models in this study.

Second, the school-level datasets were collected from school principals. Accordingly, the datasets might reflect principals' personal perspectives and would not provide sufficient information about teachers. For example, the index of teacher behavior hindering learning that was used as a school-level variable to examine school climate. However, the value of the index was calculated from questionnaire collected from school principals and the value might not represent teachers' actual behaviors. Although, there is a dataset collected from teachers in PISA 2018, only 19 countries participated in teacher assessment. If more countries participate teacher assessment in the future, we can conduct a four-level HLM, which will provide quite useful information about the impacts of the teacher or class level variables on students' mathematics achievement.

Also, the study found that Information and Communication Technology (ICT) usage is positively associated with math achievement, but the study was not able to investigate which ICT resource (there were four types of resources that were spelled out below) had a strongest correlation with math achievement because ICT usage variable was measured by ICTRES, an Index constructed through responses from students to questions about possessing ICT resources. Likewise, the study also found that extra-curricular activities in school is positively associated with math achievement. However, the study did not identify which extra-curricular activity is most relevant for math achievement because the variable was measured by the index of creative extra-curricular activities in school (CREACTIV) was calculated as the total number of creative activities in school.

This study provides some directions for future study. As mentioned above, the study found that ICT usage and extra-curricular activities in school were statistically significant predictors for math achievement, but those two predictors were measured by the indices that summarized responses from students and school principals on a series of related questions in PISA 2018. Future studies can be conducted to specify ICT resources and explore the extent of difference in associations with math achievement. In PISA 2018, there were questions asking about whether students possess ICT resources among smartphones, computers, tablet computers, and E-book readers. Those items could be used in future studies to examine how the effect of each ICT resource is different. Also, future study could be conducted using specified instruments related to mathematics achievement to explore the association between extra-curricular activities in school and mathematics achievement. In PISA 2018, types of extra-curricular activities in school were listed as follow: 1) band, orchestra or choir, 2) school play or school musical, 3) school yearbook, newspaper or magazine, 4) volunteering or service activities, 5) book club, 6) debating club or debating activities, 7) art club or art activities, 8) sporting team or sporting activities, 9) lectures and/or seminars, 10) collaboration with local libraries, and 11) collaboration with local newspapers. Future research can be used those items to examine which extra-curricular activity is the most important predictor of math achievement.

In addition, the study found that class size is positively associated with math achievement after controlling for other predictors in the model. That is, the larger the class size, the higher the math achievement. Since this contradicts prior findings such as the Tennessee class size experiment (Mosteller, 1995), more research needs to be conducted to examine the ideal class size for math achievement, though the current PISA study was for students in grade seventh and above and Tennessee experiment was for elementary school pupils. PISA 2018 measured the class size of school by using the item was categorized into nine groups as follow: 1) 15 students or fewer, 2) 16-20 students, 3) 21-15 students, 4) 26-30 students, 5) 31-35 students, 6) 36-40 students, 7) 41-45 students, 8) 46-50 students, and 9) more than 50 students. Future researchers could examine which group of the class size is most significantly associated with math achievement.

Also, the study found that the country-mean resilience self-efficacy had a negative association with country-mean students' math achievement while resilience self-efficacy had a positive association with students' math achievement. I interpreted the results that there was a shift of meaning occurs in resilience self-efficacy when it was aggregated as the country-level mean. That is, the country-mean resilience self-efficacy represented to the cultural context of country. Then, it was found that East Asian countries generally showed low country-mean resilience self-efficacy while those countries showed high country-mean math achievement. Future studies could be investigated to explore factors related to resilience self-efficacy. Cultural and national characteristics of education such as competitive environment, national system of education, and college enrollment rate could be explored to help to explain predictors associated with resilience self-efficacy.

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APPENDICES

Appendix A- Items used to create student-level independent variables

Construct	PISA 2018 Item Name	Item Questionnaire	Options
Parental education level	ST005Q01TA	What is the <highest level of schooling> completed by your mother?	1= ISCED level 3A 2= ISCED level 3B, C 3= ISCED level 2 4= ISCED level 1 5= she did not complete ISCED level 1
	ST005Q01TA	Does your mother have this qualification? <ISCED level 6> (incl. higher qualifications at level 5A in some countries)	1= Yes 2= No
	ST006Q01TA	Does your mother have this qualification? <ISCED level 5A> (excl. higher qualifications at level 5A in some countries)	
	ST006Q02TA	Does your mother have any of the following qualifications? <ISCED level 5B>	
	ST006Q03TA	Does your mother have any of the following qualifications? <ISCED level 4>	
	ST006Q04TA	What is the <highest level of schooling> completed by your father?	1= ISCED level 3A 2= ISCED level 3B, C 3= ISCED level 2 4= ISCED level 1 5= she did not complete ISCED level 1

	ST007Q01TA	Does your father have this qualification? <ISCED level 6> (incl. higher qualifications at level 5A in some countries)	1= Yes 2= No
	ST008Q01TA	Does your father have this qualification? <ISCED level 5A> (excl. higher qualifications at level 5A in some countries)	
	ST008Q02TA	Does your father have any of the following qualifications? <ISCED level 5B>	
	ST008Q03TA	Does your father have any of the following qualifications? <ISCED level 4>	
ICT usage	ST011Q05TA	In your home: Educational software	
	ST011Q06TA	In your home: A link to the Internet	
	ST012Q05NA	How many in your home: <Cell phones> with Internet access (e.g. smartphones)	
	ST012Q06NA	How many in your home: Computers (desktop computer, portable laptop, or notebook)	
	ST012Q07NA	How many in your home: <Tablet computers> (e.g. <iPad>, <BlackBerry PlayBook>)	
	ST012Q08NA	How many in your home: E-book readers (e.g. <Kindle>, <Kobo>, <Bookeen>)	
Parents' emotional support	ST123Q02NA	Thinking about <this academic year>: My parents support my educational efforts and achievements.	1= Strongly disagree 2= Disagree 3= Agree 4= Strongly agree
	ST123Q03NA	Thinking about <this academic year>: My parents support me when I am facing difficulties at school.	
	ST123Q04NA	Thinking about <this academic year>: My parents encourage me to be confident.	

Sense of belonging in school	ST034Q01TA	Thinking about your school: I feel like an outsider (or left out of things) at school.	1= Strongly disagree 2= Disagree 3= Agree 4= Strongly agree
	ST034Q02TA	Thinking about your school: I make friends easily at school.	
	ST034Q03TA	Thinking about your school: I feel like I belong at school.	
	ST034Q04TA	Thinking about your school: I feel awkward and out of place in my school.	
	ST034Q05TA	Thinking about your school: Other students seem to like me.	
	ST034Q06TA	Thinking about your school: I feel lonely at school.	
Resilience self-efficacy	ST188Q01HA	Agree: I usually manage one way or another.	1= Strongly disagree 2= Disagree 3= Agree 4= Strongly agree
	ST188Q02HA	Agree: I feel proud that I have accomplished things.	
	ST188Q03HA	Agree: I feel that I can handle many things at a time.	
	ST188Q06HA	Agree: My belief in myself gets me through hard times.	
	ST188Q07HA	Agree: When I'm in a difficult situation, I can usually find my way out of it.	
Mastery goal orientation	ST208Q01HA	How true for you: My goal is to learn as much as possible.	1= Not all true of me 2= Strongly true of me 3= Moderately true of me 4= Very true of me
	ST208Q02HA	How true for you: My goal is to completely master the material presented in my classes.	
	ST208Q04HA	How true for you: My goal is to understand the content of my classes as thoroughly as possible.	
Fear of failure	ST183Q01HA	Agree: When I am failing, I worry about what others think of me.	1= Strongly disagree

			2= Disagree 3= Agree 4= Strongly agree
	ST183Q02HA	Agree: When I am failing, I am afraid that I might not have enough talent.	
	ST183Q03HA	Agree: When I am failing, this makes me doubt my plans for the future.	
Occupational aspiration	ST114Q01TA	What kind of job do you expect to have when you are about 30 years old?	Open-ended question
Belief in the value of school	ST036Q05TA	Thinking about your school: Trying hard at school will help me get a good job.	1= Strongly disagree 2= Disagree 3= Agree 4= Strongly agree
	ST036Q06TA	Thinking about your school: Trying hard at school will help me get into a good <college>.	
	ST036Q08TA	Thinking about your school: Trying hard at school is important.	
	ST036Q06TA	Thinking about your school: Trying hard at school will help me get into a good <college>.	
	ST036Q08TA	Thinking about your school: Trying hard at school is important.	
Growth mindset	ST184Q01HA	Your intelligence is something about you that you can't change very much.	1= Strongly disagree 2= Disagree 3= Agree 4= Strongly agree

Appendix B- Items used to create school-level independent variables

Construct	PISA 2018 Item or Index Name	Item Questionnaire	Options
School locale	SC001Q01TA	Which of the following definitions best describes the community in which your school is located?	1= A village 2= A small town 3= A town 4= A city 5= A large city
Type of school	SCHLTYPE	School Ownership	1= Private Independent 2= Private Government-dependent 3= Public
Class size	CLSIZE	Class size	13= 15 students or fewer 18= 16-20 students 23= 21-25 students 28= 26-30 students 33= 31-35 students 38= 36-40 students 43= 41-45 students 48= 46-50 students 53-=More than 50 students
The proportion of fully certified teachers	SC018Q02TA01	Teachers <fully certified> by <the appropriate authority>: Full-time	Input number
Extra-curricular activities	SC053Q01TA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Band, orchestra or choir	1= Yes 2= No
	SC053Q02TA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: School play or school musical	
	SC053Q03TA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: School yearbook, newspaper [...]	
	SC053Q04TA	<This academic year>, activities offered to <national modal grade	

		for 15-year-olds>: Volunteering [...]	
	SC053Q12IA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Book club	
	SC053Q13IA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Debating club or debating [...]	
	SC053Q09TA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Art club or art activities	
	SC053Q10TA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Sporting team or sporting [...]	
	SC053Q14IA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Lectures and/or seminars [...]	
	SC053Q15IA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Collaboration with local libraries	
	SC053Q16IA	<This academic year>, activities offered to <national modal grade for 15-year-olds>: Collaboration with local newspapers	
	SC053D11TA	<This academic year>,follow. activities/school offers<national modal grade for 15-year-olds>? <country specific item>	
Student behavior hindering learning	SC061Q01TA	Extent to which student learning is hindered by: Student truancy	1= Not at all 2= Very little 3= To some extent 4= A lot
	SC061Q02TA	Extent to which student learning is hindered by: Students skipping classes	
	SC061Q03TA	Extent to which student learning is hindered by: Students lacking respect for teachers	
	SC061Q04TA	Extent to which student learning is hindered by: Student use of alcohol or illegal drugs	

	SC061Q05TA	Extent to which student learning is hindered by: Students intimidating or bullying other students	
	SC061Q11HA	Extent to which student learning is hindered by: Students not being attentive	
Teacher behavior hindering learning	SC061Q06TA	Extent to which student learning is hindered by: Teachers not meeting individual students' needs	1= Not at all 2= Very little 3= To some extent 4= A lot
	SC061Q07TA	Extent to which student learning is hindered by: Teacher absenteeism	
	SC061Q08TA	Extent to which student learning is hindered by: Staff resisting change	
	SC061Q09TA	Extent to which student learning is hindered by: Teachers being too strict with students	
	SC061Q10TA	Extent to which student learning is hindered by: Teachers not being well prepared for classes	

Appendix C–Types of University Admission Procedure

Country	University Admission Procedures	Descriptions
Albania	Secondary leaving examinations (SLE)	Students have to complete the State Matura exam (*Matura Shtetërore*), which refers to the secondary school exit exam (Maghnouj et al., 2020).
Baku (Azerbaijan)	Entrance examinations (EE)	Students take the entrance examination which is administered by the national government. The entrance exam was offered once a year until 2017 but now is offered twice a year (Isaxanli, 2005)
Argentina	No examinations (NE)	There are no standard entrance examinations for applying to higher education institutes, thus university admissions are arranged by each university (Theiler, 2005).
Australia	Multiple examinations (ME)	Most universities in Australia consider the Australian Tertiary Admission Rank (ATR) which is given to secondary school students and ranges from 0 to 99.5 (Pilcher & Torii, 2018). Also, students need to achieve a certain level of credits in certification tests which are arranged by each state (Gale & Parker, 2013).
Bosnia and Herzegovina	No examinations (NE)	Students who complete secondary education can be accepted to any programs in higher education institutions (NUFFIC, 2007).
Brazil	Entrance examinations (EE)	Traditionally in Brazil, individual universities have their own entrance exams which are called the *vestibular*. Since 2009, the Brazilian Ministry of Education has used the Exam Nacional do Ensino Médio (ENEM) as another official university entrance exam and many universities in Brazil have (Stanek, 2013).
Bulgaria	Entrance examinations (EE)	In Bulgaria, individual higher education institutions administrate their own entrance exams which are called the *konkursen* (NUFFIC, 2020).
Belarus	Entrance examinations (EE)	Candidates take admission exams which are called Centralized Testing (CT) (Belarus.by, n.d.).

Chile	Entrance examinations (EE)	Students take the university entrance exam which is called PSU (*Prueba de Selección Universitaria*, "University Selection Test") (NUFFIC, 2015).
Chinese Taipei	Entrance examinations (EE)	Admission to universities require the entrance exam called the General Scolastic Ability Test (GSAT) which is administered by the nonprofit organization called the College Entrance Examination Center (CEEC) (College Entrance Examination Center, n.d.).
Colombia	Entrance examinations (EE)	Students who achieved Bachiller Académico certificate during secondary schools can apply for higher education through the state exam called Examen de Estado (NUFFIC, 2015).
Costa Rica	Entrance examinations (EE)	The entry requirement for higher education is getting secondary school qualification called Bachiller en Educación Media and students who completed the secondary school can take entrance exams that administrated by each university (NUFFIC, 2018).
Croatia	Secondary leaving examinations (SLE)	In Croatia, students who complete the State Matura Exam which is a secondary school leaving examination can apply higher education (World Education Network, n.d.-a).
Czech Republic	Multiple examinations (ME)	Students who would like to apply higher education institutions must complete the Maturita exam which is the universal leaving qualification of secondary schools (OECD, 2022). Then, students take the entrance exam which is administrated by each university.
Dominican Republic	Secondary leaving examinations (SLE)	Most universities require the secondary school diploma, the *bachillerato* which consists of several exams (AACRAO, n.d.).
Estonia	Secondary leaving examinations (SLE)	In principle, secondary education certificates are required to apply universities (NUFFIC, 2018).
Finland	Multiple examinations (ME)	At the end of secondary educations, students should pass the Finnish Matriculation Examination to qualify for applying university admission. Universities select students based on their score from the Matriculation exam and

		entrance exams that are administered by each university (Kim, 2020).
France	Secondary leaving examinations (SLE)	Students who pass the *Baccalauréat* (French national secondary leaving examination) can apply to higher education (NUFFIC, 2016).
Georgia	Multiple examinations (ME)	Students who would like to enter universities should take the secondary leaving examination called the Secondary Graduation Examination (SGE) to get certified in secondary graduation and take the university entrance exam called the Unified Entry Examination (UEE) (Ruochen et al., 2019).
Germany	Standardized Aptitude Tests (SAT)	Universities require scores of Gymnasiums and Abitur. Gymnasium scores indicate scores that have achieved from secondary school. Abitur refers to the higher education entrance examination (Studying in Germany., n.d.)
Greece	Multiple examinations (ME)	Both the *Apolytirio Genikou Lykeiou* (secondary school certificate) and *Bebaiosi Prosbasis* (certificate of higher education admission) are required to enter Greek higher education (NUFFIC, 2020).
Hong Kong	Entrance examinations (EE)	Students take the Hong Kong Diploma of Secondary Education Examination (HKDSE) which is the university entrance exam (Hong Kong Examinations and Assessment Authority, n.d.).
Iceland	Secondary leaving examinations (SLE)	Students who want to enter universities must complete the matriculation examination and obtain Stúdentspróf which is educational diploma in Iceland (NUFFIC, 2015).
Indonesia	Multiple examinations (ME)	*Ijazah Sekolah Menengah Atas* which is the secondary school certificate and *Surat Keterangan Hasil Ujian Nasional* which is the state examination are both required for applying university (NUFFIC, 2017).
Italy	Secondary leaving examinations (SLE)	After the five years of secondary education, students take the Matura exam, and the certificate of the exam is required for admission to higher education (NUFFIC, 2015).

Japan	Entrance examinations (EE)	Two university entrance examination are required in Japan: 1) the National Center Test for University Entrance Admission which is organized by the National Center for University Entrance Examinations, 2) Entrance examinations administered by each institution (NUFFIC, 2020).
Kazakhstan	Entrance examinations (EE)	Since 2004, a secondary school leaving examination and university entrance examination have been integrated into the Unified National Test (UNT) World Education Network (n.d.-c).
Jordan	Secondary leaving examinations (SLE)	The achievement on the General Secondary Education Certificate Examination is the main criterion for admission to higher education (Education Encyclopedia, n.d.)
Korea	Entrance examinations (EE)	The College Scholastic Aptitude Test (CSAT), the national college entrance examination authorized by the Korean government is required to admission to higher education (Park, 2014)
Malaysia	Entrance examinations (EE)	Students who would like to enter higher education should take the Malaysian Higher School Certificate, *Sijil Tinggi Persekolahan Malaysia (STPM)* which is pre-university examination (NUFFIC, 2015).
Malta	Secondary leaving examinations (SLE)	The Matriculation Certificate examinations are required to admission to higher education (Education in Malta, 2021)
Mexico	Entrance examinations (EE)	Most universities in Mexico require the score of the EXANI II (*Examen Nacional de Ingreso a la Educación Superior*), the national standardized higher education entrance exam (NUFFIC, 2015).
Moldova	Secondary leaving examinations (SLE)	Students hold the *Diplomă de bacalaureat* which is the secondary leaving certification can enter higher education (NUFFIC, 2019).
Montenegro	Secondary leaving examinations (SLE)	Students who would like to enroll higher education should submit secondary school leaving certificate and Matura, secondary school exit examination (ERASMUS, n.d.))

Morocco	Secondary leaving examinations (SLE)	*Baccalauréat*, a secondary school leaving certificate should be achieved to access to higher education in Morocco (MERIC-Net, 2019).
Netherlands	Secondary leaving examinations (SLE)	A *Voorbereidend wetenschappelijk onderwijs* (VWO) diploma, meaning pre-university diploma is required for admission higher education. Students should take a matriculation exam to achieve VWO (NUFFIC, n.d.).
New Zealand	Secondary leaving examinations (SLE)	The National Certificate of Educational Achievement (NCEA) which is the main national qualification for secondary education is required for admission to university education (NZQA, n.d.).
Panama	Entrance examinations (EE)	All official universities in Panama are required to take admissions tests administered by each institution (RecoLATIN, 2019).
Peru	Entrance examinations (EE)	Students should take a university entrance exam, or a competitive exam administrated by individual universities (World Education Network, n.d.-b))
Philippines	Entrance examinations (EE)	The National College Entrance Examination (NCEE) is required to higher education admission (Education Encyclopedia, n.d.-b).
Poland	Secondary leaving examinations (SLE)	Students should take maturity exam, called *egzamin maturalny* for admission to universities (Bitel, A et al., 2021).
Qatar	Secondary leaving examinations (SLE)	A secondary education certification, *Thanawaya Aam Qatari* must be achieved for admission to higher education (World Education Network, n.d.-c)
Romania	Entrance examinations (EE)	Students must take the entrance examination called the *Diploma de Bacalaureat* for admission to universities (Sedgwick, 2003).
Russian Federation	Entrance examinations (EE)	The Uniform State Exam (EGE) is requirement for admission to higher education in Russia (NUFFIC, 2019).

Saudi Arabia	Standardized Aptitude Tests (SAT)	The requirements for admission to higher education in Saudi Arabia is the General Secondary Education Certificate and General Aptitude Test (GAT) which is the aptitude tests for measuring students 'analytical and deductive skills (Alnahdi, 2015).
Serbia	Multiple examinations (ME)	Since Serbia lacks a standardized national university entrance examination, students should take multiple examinations that administered by each higher educational institution (Maghnouj et al., 2020)
Singapore	Entrance examinations (EE)	The Singapore-Cambridge General Certificate of Education Advance Level (GCE A-Level) which is a national qualification examination for universities is the major requirement for admission to higher education in Singapore (SEAB, n.d.)
Slovak Republic	Multiple examinations (ME)	The secondary school-leaving examination and entrance examination are main requirements for admission to higher education (StudentNews Group, n.d.)
Slovenia	Secondary leaving examinations (SLE)	The major requirement for admission to higher education is a secondary school leaving exam, *Matura* (McGrath et al., 2014).
Spain	Entrance examinations (EE)	Students' GPA in Baccalaureate which is the upper secondary education and university entrance exam, *Pruebas de Acceso a la Universidad* (PAU) are required for admission for higher education in Spain (OECD, 2022)
Switzerland	Secondary leaving examinations (SLE)	*Matura*, a secondary leaving examination is the main requirement for admission to higher education (Lyceum Alpinum Zuoz, n.d.)
Thailand	Multiple examinations (ME)	Students must apply to universities through the Thai University Central Admission System (TCAS) and submit results of the Ordinary National Education Test (Onet), the General Aptitude Test (Gat), the Professional Aptitude Test (Pat) and other tests if necessary (The Nation Thailand, 2017)

United Arab Emirates	Standardized Aptitude Tests (SAT)	The EmSAT, which is the computer based national standardized test is the main requirement for applying higher education. The schedule of the test is flexible and subjects of the EmSAT include English, Arabic, mathematics, physics, chemistry, and biology (Laurels Training Institute, n.d.)
Turkey	Multiple examinations (ME)	Students must hold a secondary school diploma and should take two central entrance examinations: TYT, *Temel Yeterlilik Testi* (Basic Proficiency Test) and YKS, *Yükseköğretim Kurumları Sınavı* (Higher Education Institutions Exam) (NUFFIC, n.d.-b).
United Kingdom	Secondary leaving examinations (SLE)	The Universities and College Admissions Service (UCAS) manages admission to higher education in U.K. and students should obtain results from the General Certificate of Education (GCE) Advanced Level, also called A-Level which is the main secondary school leaving qualification in England (Magaziner, 2016),
United States	Standardized Aptitude Tests (SAT)	Most universities in U.S. consider students' performance on the standardized aptitude test (SAT) or the ACT, which is a standardized test for measuring students' readiness for university (NUFFIC, n.d.-a))
Uruguay	Secondary leaving examinations (SLE)	Generally, students who hold bachillerato which is the secondary school leaving certificate can apply higher education (Paulo et al., 2016)
B-S-J-Z (China)	Entrance examinations (EE)	The national entrance examination called *gaokao* is the main requirement of admission for higher education in China (NUFFIC, n.d.-a)