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THE EFFECTS OF SCHOOL MATHEMATICS RESOURCES ON STUDENTS' INTENTION TO STUDY MATHEMATICS OVER OTHER SUBJECTS: MULTILEVEL MEDIATION STRUCTURAL EQUATION MODELING

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THE EFFECTS OF SCHOOL MATHEMATICS RESOURCES ON STUDENTS' INTENTION TO STUDY MATHEMATICS OVER OTHER SUBJECTS: MULTILEVEL MEDIATION STRUCTURAL EQUATION MODELING

By Eunhye Cho

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Abstract

Increasing students' intentions to pursue mathematics-intensive careers is an urgent priority in the United States. To foster these intentions among marginalized student groups, such as immigrant students, and achieve equity in their career options, a critical question is whether we should allocate a greater proportion of school resources to mathematics over other subjects. The aims of this dissertation study were, first, to conceptually model and statistically evaluate how a school environment that prioritizes mathematics over other subjects might influence students' intentions to pursue mathematics over other academic subjects in the long term, and second, how this relationship is mediated by students' mathematics pursuit attitudes, subjective norms, and perceived behavior (Ajzen, 1991), and moderated by their immigrant standing.

The data for this study stemmed from the U.S. 2012 Programme For International Student Assessment Academic & Science (PISA) Student Questionnaire and School Questionnaire. A predictive mean matching technique was used to impute missing data that would resemble observed data. A 2-1-1 multilevel mediation Structural Equation Modeling (SEM) was implemented to accurately measure a school-level effect and student-level effect of the relationship of the examined constructs and to test the hypothesized model for the total sample. In order to compare immigrant student group and non-immigrant student group in the path model, multiple group path analysis was conducted.

The results of the multilevel SEM model for the total sample presented that, at the school level (level 2), the school's mathematics resources had no statistically significant direct and indirect effects on aggregated students' intentions to pursue mathematics over other subjects. However, at the student level (level 1), students' experiential and instrumental attitudes toward the pursuit of mathematics were positively related to students' intentions to pursue mathematics over other subjects. The results of the multiple group path analysis comparing immigrant and non-immigrant student groups also found that the school's mathematics resources had no statistically significant direct and indirect effects on students' intentions to pursue mathematics over other subjects. However, a statistical difference in the overall path model of these two groups was found. The implications of this study for researchers, educators, and policymakers were discussed.

DEDICATION

Dedicated to My Mother, Teacher Extraordinaire and Karin (deceased)

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CHAPTER ONE

PROBLEM STATEMENT

Immigrants to the United States have changed the demographics of U.S. schools. One in four children in the U.S., accounting for more than 18 million children, has at least one foreign-born parent (Lou, 2020). The schools that serve the children of immigrants have been reported to have a varying range of school resources (Hillmert, 2013; Olivos & Mendoza, 2010; Stanton-Salazarm & Dornbusch, 1995), which may impact students' motivation to study particular subjects and their overall school performance (e.g., Breda & Napp, 2019; Chiu & Khoo, 2015). Moreover, the long-standing unequal distribution of school resources (e.g., qualified teachers) in the United States has been exacerbated by COVID-19 (Van Lancker & Parolin, 2020). Inadequate resources in some schools have aggravated existing achievement and opportunity gaps and reduced students' engagement in learning (Dorn et al., 2020). These devastating effects of the pandemic have caused researchers to revisit the topic of the impact of school resources on students' academic motivation.

A new approach to examination of the relationship between school resources and students' academic motivation can be derived from the lessons learned in previous research and by addressing the limitations of prior studies. The existing literature represents the field's attention to the effects of school resources on students' motivation for studying particular subjects, for example, mathematics or English, rather than on their motivation for both subjects in relation to each other and how their different levels across subjects are influenced by amount and distribution of school resources. To investigate the relative levels of motivation between these critical different subjects, I revisited the idea in social psychology that people tend to think of themselves as either math persons or verbal persons but not both (Marsh & Hau, 2003; Marsh, 1986). A student who thinks of her/himself as one type of person is likely to gravitate toward that subject when given a choice. At the school level, there may also often be a policy of favoring one over the other – Some schools have outstanding teachers in one subject area than other areas (Hallinan, 1994) -, suggesting that students motivated to study the favored subject will be better served than students motivated to study the less favored subject as well as that students' interests will be directed to the favored subject.

This study is based on the notion of finiteness of resources and that poorly supported schools must allocate their resources in conditions of scarcity. Thus, schools that invest their resources more in math instruction are likely to allocate fewer resources to teaching other subjects and vice versa. Awareness of students' identity formation (math person or verbal person) and of adequacy and allocation resources can provide insight into realities that have not much been highlighted in the previous studies (Breda & Napp, 2019).

Thus, this study is an examination of the extent to which school math resources influence students' motivation to study math over other subjects. Additionally, I compared this relation across two groups categorized by immigration status: immigrant students vs. non-immigrant students. I hypothesize that these two groups may show differences in the strength of the path of the variables considering that immigrant students have a statistically significantly higher odds of plans to major in a STEM field at college than non-immigrant students (Chachashvili-Bolotin et al., 2019; Porche et al., 2016). To further examine the relationship between immigrant status and motivation to study mathematics, I employed the theory of planned behavior (Ajzen, 1991) as a theoretical framework. This theory posits that the three socio-cognitive determinants predict intentions: attitudes, subjective norms, and perceived control over behavior. These are used to explain the variance in the relation between school math resources and students' intentions to pursue study of math. The data set for this study was drawn from the U.S. 2012 Programme for International Student Assessment (PISA), which was the year in which, the PISA survey collected data on variables that are part of the theory of planned behavior. A total sample of 1,108 student from 36 schools were analyzed in this study.

In this study, I propose using a multilevel mediation structural equation modeling to estimate this model in which independent variables are at the school level and the other variables are at the individual level. I use a multilevel framework as the PISA data have a nested data structure (i.e., students are nested in schools). Failure to address hierarchical nature results in an unreliable estimation of the school math resources' effect on students' math motivation and intention (Raudenbush & Bryk, 1992). However, to my best knowledge, most analyses in examining the theory of planned behavior's constructs in the math education field did not consider the hierarchical structure of the data (Arditzoglou & Crawley III, 1992; Blanchard et al., 2003; Burrus & Moore, 2016; Foltz, Foltz, & Kirschmann, 2015; Hagger & Hamilton, 2020; Lipnevichet al., 2011; Lipnevich et al., 2016). My dissertation is unique in that it takes a school-level effect and a student-level effect into account to test the central hypotheses of my research.

This study makes three major contributions – theory, practice, and methodology. Theoretically, it fills a gap in the literature on the effect of *relative* levels of school resources on students' math motivation. Students' mathematics preferences over English have been understudied compared to measuring their interest in each subject separately. This dissertation also extends the theory of planned behavior by applying it to the math education field, where it has been rarely employed. In this process, school math resources are integrated as a predictor of students' math intentions to explain the variance unaccounted for in the model. Also comparing culturally different groups can extend empirical findings of the theory by capturing the measurement variance. This study is timely and has implications for policy, given the necessity of the schools' resource redistribution due to the COVID-19 Pandemic. This dissertation also can provide practical implications that may guide educators to create intervention strategies that correspond to each factor of the research model. Methodologically, it provides a sophisticated multilevel mediation SEM and multiple group SEM.

The present chapter illuminates the background of this dissertation topic and my motivation for pursuing it. This chapter begins with the social background and theoretical background of the study. Next, the research objectives of this dissertation are described. The chapter concludes with a discussion of the theoretical, empirical, and practical implications of this study and a description of future chapters.

Social Background: U.S. Immigrants and Their Intentions to Study Math Over Other Subjects

Why is it important to understand students' intentions to study math over other subjects in the U.S. context? Why is it necessary to connect this understanding to students' immigrant status? Addressing these questions can help schools in the U.S. prepare students for Science, Technology, Engineering, and Mathematics (STEM) fields, particularly those that are mathematics-intensive.

Over the past decade, the demand for qualified workers in the STEM industries in the United States has rapidly increased, situating it as a linchpin for economic growth. Employment in STEM occupations increased by 10.5 percent between May 2009 and May 2015, more than twice the 5% growth in non-STEM occupations (Fayer et al., 2017). Among the STEM occupations, math-intensive careers such as statisticians, computer engineers, and more recently, data scientists, are expected to increase by 28% from 2014 to 2024 in the United States, which is substantially higher than the expected average increase for all occupations of 6%. Concomitantly, policies have been implemented to attract immigrant-origin workers in the math-intensive fields by recruiting foreign-born graduate students or issuing temporary visas to foreign-born STEM experts. As a result of these strategies, immigrant-origin workers constitute 26% of those in U.S. math-intensive careers (American Immigration Council, 2017).

While some policies have attended to these temporary immigrant-origin workers' contributions, the education of immigrant-origin K-12 students has been neglected in the current conversation (Porche et al., 2016). Although the U.S. government emphasized encouraging minority K-12 students' access to math-related fields, the focus was on students who were historically underrepresented in the STEM field, such as women and racial minority groups, but not specifically on immigrant-origin students (Committee on STEM Education, 2018), who are estimated to constitute one-third of the nation's schoolchildren younger than 17 by 2050 (Maxwell, 2014). Failure to address their motivation for learning math may lead to problematic consequences in national competitiveness and policy development.

The notion of verbal and math self-concepts, conceptualized by social psychologist Marsh (1986), can be used to explain why students choose to study one subject over another. Because a student see her/himself as either a math or verbal person, the two self-concepts are relatively uncorrelated at an intra-level (Marsh, 1986). For example, immigrant students who tend to perform better in math than other subjects, or whose parents and peers emphasize succeeding in math, can be more likely to prioritize studying math over other subjects. However, previous studies have seldom statistically measured the relationship between immigrant students' motivation and their pursuit of math-intensive careers (Porche et al., 2016; Schleicher, 2006). Thus, the aim of this dissertation study is to extend existing research by examining students' intentions to study math over other subjects according to immigrant status (i.e., immigrant students vs. non-immigrant students).

Theoretical Background: Extending the Theory of Planned Behavior and School Math Resources

Students' math related academic intentions can be examined in terms of theories that conceptualize the factors that influence intentions. Over the past 35 years, various constructs that influence academic motivation and intention have been investigated through different theoretical lenses (Koenka, 2020). One primary theory is the theory of planned behavior, which identifies the predictors of an individual's behavior (Ajzen, 1991; Ajzen & Icek Ajzen, 2006). These studies have found that the best predictors of behavior are intentions, and intentions can be analyzed in terms of three motivational factors: pursuit attitudes, subjective norms, and perceived behavioral control. While the theory of planned behavior has proved its validity through empirical research, the theory itself has the limitation that it focuses solely on socio-cognitive determinants and neglects other factors that may explain the unaccounted variance in the model (Ajzen, 1991; Hamilton & White, 2012). For example, the theory does not take socio-structural factors (e.g., SES, gender) and socio-cultural factors (e.g., math education) into account as crucial determinants (Hagger & Hamilton, 2020; Schüz, 2017). In the examination of the students' math pursuit intentions, integrating additional variables such as socio-structural and socio-cultural factors may increase the model's explanatory capability across contexts and populations.

In the realm of math education, the influence of school math resources for math instruction on students' math learning has been a major focus in the policy discourse and scholarly literature. Since the contentious findings of the Coleman report of 1966 (that school resources were less associated with student achievement than family background), a substantial body of research has emerged in which the impact of school resources is measured according to a wide array of school resources characteristics. As one characteristic of school resources, the qualifications of math teachers have been investigated for the last several decades, including types of teacher certification (Goldhaber & Brewer, 2000); teachers' levels of content knowledge, mostly indexed by the number of courses taken in the field (Darling-Hammond, 2000); and their years of teaching experience (Murnane & Phillips, 1981; Rivkin et al., 2005).

A major issue with regard to math teacher qualification is a long-standing shortage in the supply of teachers in the U.S. education system (e.g., Adnot et al., 2017; Liu et al., 2008). While the shortage of math teachers intensified concerns, the U.S. government passed the No Children Left Behind Act in 2001, which required teachers to be "highly qualified," that is, have full certification, a bachelor's degree, and sufficient content knowledge (Smith et al., 2005). More strict hiring requirements exacerbated the lack of math teachers, and a subsequent new policy called Every Student Succeeds Act of 2015 (ESSA) rescinded the provision of a bachelor's degree. In light of loosened teacher hiring requirements at the federal level, scholarly discussion questions increased about the extent to which teacher qualifications can influence students' mathematic learning (Close et al., 2018).

The large body of research in which the effects of the supply and qualifications of math teachers were measured sheds light on students' math achievement. However, the focus of this study is to measure students' relative intentions to study math over English, specifically, on the motivation factors that are relatively neglected in the previous studies (Chiu & Khoo, 2005). Further, this study addresses the gap in supply between math teachers and English teachers. The unequal distribution of certified teachers was found to be associated with students' low scores in math, reading, and science (Chiu & Khoo, 2005). In this study, the aim was to estimate the extent of the school's focus on math over English in their resource distribution and its ability to predict students' motivation for math over English.

Another critical dimension of the current study, which can extend the model, is its measurement of model parameters in different subpopulations. As stated in the previous section, immigrant students' math intention is the focal interest of this study. In studies that applied the theory of the planned behavior, samples representing different backgrounds had differences in the robust predictors of their math achievement and intentions to study math (Lipnevich et al., 2011; Lipnevich et al., 2016; Porche et al., 2016). Immigrant and non-immigrant groups may have different model parameters. Thus, the current study accounts for variations in how a school's math resources' influence on students' intentions to pursue math over other subjects by considering the theoretical constructs (e.g., math pursuit attitudes, subjective norms, perceived behavioral control) and compare the paths of the model among groups of interest.

Purpose of the Study

This study's primary purpose is to examine the mediating role of socio-cognitive determinants (i.e., mathematics pursuit attitudes, subjective norms, perceived behavioral norms) and in the relation between school mathematics resources and students' intentions to study mathematics over other subjects. Toward this end, the following research questions are explored:

1. How does a school that prioritizes resources for school math over other subjects (regressors x) influence students' exhibiting intentions to pursue math over other subjects (outcome y)?
2. Is the resulting effect mediated by students' math pursuit attitudes, subjective norms, perceived behavioral control (mediators m)

3. Does this effect change with students' immigrant standing (moderator *z*)?"

Significance of Study

This dissertation study is undertaken to advance understanding of students' motivation to study math over other subjects both theoretically and methodologically. From a theory perspective, this study extends the theory of planned behavior by adding a predictor of school resources to students' math motivation. The socio-cultural factor, which has mostly been overlooked by previous researchers, is shown here to help explain the academic motivation of students from diverse backgrounds.

The study also identifies the relationship of the constructs of the theory of planned behavior., which helps to articulate the theory. In developing the theory of planned behavior, Ajzen (1991) claimed that the relationship was not accurately identified, even though each of the three components has its own salient behavioral, normative, and control beliefs about the behaviors. Previous empirical studies built on this theory have shown inconsistent findings of the relationship of the constructs. In some cases, attitudes were salient in predicting students; achievement (Lipnevich et al., 2016), while students' choice of major was under subjective norms control (Foltz et al., 2015). The current study set the hypothesis to identify the extent to which each of the three socio-cognitive determinants can explain intentions. This approach will clarify the relation of the constructs.

The study also makes this model more nuanced by adding a new dimension of students' immigration standing: immigrant students vs. non-immigrant students. The examination of the moderating effect of immigration standing will draw attention to which group is influenced by which factor in the students' pursuit of math.

Moreover, the current study reflects the reality that students must choose the subject in which to invest their time, such as selecting math over other subjects. This approach has been underexplored in the extensive literature that focuses on students' motivation for one subject rather than comparing students' motivation between subjects.

This study makes a methodological contribution to empirically test the theory of planned behavior by proposing a multilevel moderated mediation structural equation modeling (SEM). This study demonstrates the application of multilevel SEM in consideration of multilevel data structure and multiple mediators, which has not been attempted in studying the theory of planned behavior in the math education field to the best of my knowledge. Additionally, a multiple group path analysis was employed to test the model parameters' invariance between an immigrant student group and non-immigrant student groups.

The results of this dissertation will provide practical implications for educators, researchers, and policy makers who are interested in developing intervention strategies. The modifiable determinants of math intentions identified in this study can be targets for intervention using students' behavior change techniques (Hagger & Hamilton, 2020).

Definition of Terms

School Math Resource: Label used in this work to refer to the school resources particularly devoted to math with a focus on math teacher allocation. In this work, it was computed involving (1) the proportion of math teachers in the teaching staff; (2) the proportion of math teachers that are qualified in the total teaching staff that is qualified, as used in the works of Breda and Napp (2019).

Math pursuit attitudes: The construct reflecting how favorable one feels toward performing mathematics. Two dimensions of the math pursuit attitudes: (1) experiential attitude, and (2) instrumental attitudes (Fishbein & Ajzen, 2011).

Math subjective norms: The construct reflecting a person's perceived social pressure to perform mathematics. This study involves two dimensions of math subjective norms, one influenced by friends and one influenced by parents (Fishbein & Ajzen, 2011).

Perceived behavioral control: The construct reflecting a person's perceived capability to have control over her/his math performance (Fishbein & Ajzen, 2011).

Math pursuit intention over other subject intention: Label used in this work to refer to a person's willingness to pursue math over other subjects in the long term. This study calculates three dimensions of math pursuit intention over other subject intention: (1) willingness to take more math courses than other subjects at high school; (2) willingness to major in a subject in college that requires math-intensive skills; and (3) willingness to pursue math-intensive careers over other careers that are not closely related to math skills.

Multiple imputation by chained equation (MICE): An imputation technique that handle missing data by taking a series of estimations where each variable takes its turn in being regressed on the other variables (Wulff & Ejlskov, 2017).

Predictive mean matching: One of the MICE approaches using the predicted value for a given observation to identify similar observations (Wulff & Ejlskov, 2017).

Structural equation modeling (SEM): A comprehensive statistical approach to representing, estimating, and testing a theoretical network of (mostly) linear relations between variables (Rigdon, 1998 as cited in Suhr, 2003). This approach commonly involves a measurement model and structural model.

Confirmatory factor analysis (CFA): One of the most commonly used measurement models. A multivariate statistical procedure that is used to test whether measures of a factor are consistent with a theory's understanding of the nature of that factor (Jöreskog, 1969). The model is of the following form (Lee, 1981, p. 153):

$$\Sigma = \Lambda\Phi\Lambda' + \Psi, \tag{1.1}$$

where Λ is a $p \times k$ matrix of factor loadings, Φ is a $k \times k$ symmetric matrix of factor covariances, and Ψ is a $p \times p$ diagonal matrix of unique variance.

Goodness-of-fit: A measure indicating how well a pattern of fixed and free parameters specified in the model fits the pattern of variances and covariances from a set of observations (Suhr, 2003, p. 3). Examples of fit indices are chi-square and RMSEA (Root Mean Square Error of Approximation)

Model invariance test: A test that evaluates whether survey responders from different groups interpret the same items in a similar way or not.

Structural model: A model showing the relationships between variables such as direct effect and indirect effect.

Overview of the Study

The dissertation is organized in five chapters. Following the introduction to the problem and research question, in Chapter 2, the literature relevant to the contents of the study is reviewed. This chapter begins with the framework of this study, the theory of planned behavior, followed by related studies addressing the relationships among predictors, mediators, and moderators applicable to this study. Chapter 3 provides the research model, instruments, and analytic methods of this study. The chapter includes the research hypotheses, the survey instruments, and the analytical process of analysis. Chapter 4 presents the results of the study organized by the four research questions. The chapter begins with the results of the measurement models and structural models for the total sample, followed by the results of multiple group analysis. In Chapter 5, a summary of the study, the discussion of the study's results, conclusions and implications of the study's results are discussed along with the limitations of this study and future steps.

CHAPTER TWO

REVIEW OF THE LITERATURE

The purpose of the current study is to create a model of to what extent schools' math resources affect students' intentions to study math over other subjects. Furthermore, the relationship between math motivation variables and school math resources are examined. This relationship will be compared between immigrant students and non-immigrant students.

This chapter reviews four lines of the scholarly literature that informs the current study and then presents four research hypotheses, one corresponding to each of the lines of the literature: (1) the theory of planned behavior; (2) the relationship between school math resources and students' math related academic intentions; (3) the mediating role of attitudes, subjective norms, and perceived behavioral control on the relationship between school math resources and students' math intention and; (4) the relationship between immigrant students and school math resources within the framework of the theory of planned behavior. Finally, the research model that drives the current study is presented.

The first section of the chapter reviews the theory of planned behavior, which provides the framework of the current study. The components of the theory are explicated, and the achievements and limitations of the theory as demonstrated in previous studies are discussed. Based on this discussion, the research model guiding the current study is presented and justified.

The second section of the chapter reviews a set of empirical studies of the relationship between the independent variable (school math resources)and the dependent variable (students' math intention) of the current study. Specifically, the school math resources that this study highlights is math teacher staffing and math teacher qualification. This section presents a summary of the decades of research on this relationship followed by a discussion of further research that could be conducted based on the previous literature to provide insight into the relationship between the independent variable and the dependent variable.

The third section of the chapter provides a review of empirical studies of the relationships among three motivation variables that are the components of the theory of the planned behavior: math pursuit attitudes, subjective norms, and perceived behavioral control. In the research model guiding the current study, these variables are hypothesized as mediators. In this section, the relationships found among these three variables in previous studies are discussed along with how using them as mediators in this study's model can further the scholarly discussion.

The fourth section of the chapter reviews the moderating role of immigrant standing on the relationship between school math resources and students' math intention. A comparison of the relationships between variables as identified in studies of immigrant students versus non-immigrant students will be discussed. This section presents empirical studies of the relationship between school math resources and math intentions, including, first, how school math resources have differentially affected the learning of these different groups of students' learning and, second, how intentions to study math over other subjects differ between immigrant and non-immigrant students.

The chapter concludes with a summary of empirical studies that have estimated the relationship of school mathematics resources and students' intentions in mathematics over other subjects, taking into account the moderating effect of immigrant standing and how these studies' limitations suggest the need for further theoretical and methodological considerations.

The Theory of Planned Behavior as an Underlying Framework

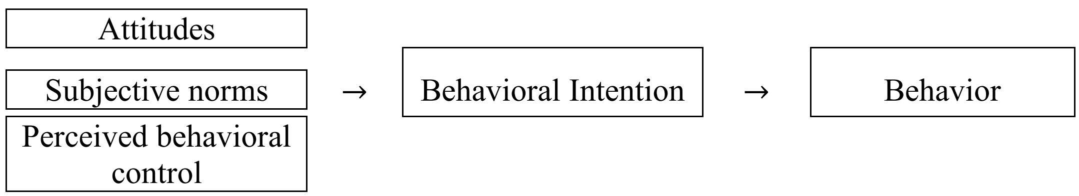
Though students' access to school math resources and their cognitive abilities are cardinal prerequisites for successful math achievement and preferences for math, these determinants do not explain all the variation among individuals in their math achievement and academic preference for math over other subjects (Floyd et al., 2003; Lipnevich et al., 2011). Students' levels of engagement, perceived value of success, and perceived capability to control their performance affect whether they choose to study math (Moore & Burrus, 2019). These socio-cognitive determinants (i.e., attitude, subjective norms, and perceived behavior control) and socio-cultural factors (i.e., math education) can explain students' math preferences. This thesis sheds light on the mediating roles of socio-cognitive determinants in examining the relationship between school math resources and students' intentions to study math over other subjects. Based on Ajzen's (1991) theory of planned behavior, I conceptualize socio-cognitive determinants as consisting of these three socio-cognitive factors (i.e., attitude, subjective norms, and perceived behavior control) and one factor of intention.

The constructs of the theory of planned behavior were originated from social psychology, where the ways that people believe, feel, and behave are influenced by the actual, imagined, perceived, or implied presence of others in society. The theory of planned behavior defines theoretical constructs of individual motivational components as determinants of the likelihood of performing a specific behavior. According to Montaño & Kasprzyk (2015), a fundamental assumption of the theory of planned behavior is that “individuals are rational actors who process information and that underlying reasons determine motivation to perform a behavior” (p. 76). These reasons determine an individual’s behavioral, normative, and control beliefs, and determine her/his attitudes, subjective norms, and perceived behavioral control. Additionally, the theory includes factors that motivate attitudes, subjective norms, and perceived behavioral control as these influence intentions to engage in a behavior.

A misconception about the theory of planned behavior is that the model's focus is primarily on rational behavior (Montaño & Kasprzyk, 2015). This misconception may come from the word “planned” in the name of the model, which connotes decision-making based on conscious reasoning. However, the term does not suggest that the reasons underlying motivation and behaviors are necessarily rational or logical.

Figure 2.1

The Theory of Planned Behavior



The theory of planned behavior consists of four constructs. The constructs are three socio-cognitive factors, including attitudes, subjective norms, and perceived behavioral control, and these lead to the fourth, behavioral intention, as illustrated in Figure 2.1. The theory of planned behavior claims that the best predictor of behavior is the intention to perform the behavior (Ajzen, 1991).

Attitudes

Attitudes toward behaviors reflect how favorable one feels toward performing specific actions. The construct of attitudes can be divided into two dimensions: experiential and instrumental attitudes (Fishbein & Ajzen, 2011). *Experiential attitudes* involve the extent to which an object or behavior is perceived as enjoyable and pleasant. For example, this construct measures how much a person likes math and perceives doing math as enjoyable and pleasant. This type of attitude represents the intrinsic value the person places on a specific behavior. In contrast, *instrumental attitudes* reflect the extent to which one perceives an object or behavior as worthwhile. That is, instrumental attitudes involve one’s perception of the utility cost of an object or behavior. For example, the construct of instrumental attitudes measures whether a student finds it useful and worthwhile to study math.

Subjective Norms

Subjective norms denote a person's perceived social pressure to perform a given behavior. According to Fishbein & Ajzen (2011), subjective norms have two dimensions: injunctive and descriptive. *Injunctive norms* refer to rules perceived as mandatory, that is, whether people whose judgements matter to one would approve or disapprove of a given behavior (Zou & Savani, 2019). For example, students whose parents compel them to study math are likely to have intentions to take math courses over other courses. *Descriptive norms* apply to behaviors that are perceived as typically performed by the people around one. For instance, having friends who work hard at math predicts a student's likelihood of taking math courses over other courses.

Perceived Behavioral Control

Cognitive self-regulation plays a vital role in predicting behavior (Ajzen, 1991). Perceived behavioral control refers to the extent to which a person perceives his/her capability to have control over the performance of behavior (Fishbein & Ajzen, 2011). Students who perceive they have high behavioral control over studying math and successfully using math are more likely to believe they are capable of doing math than students who do not. These students would consider studying math relatively easy because they have control in doing math.

Perceived behavioral control, a newly added component in the theory of planned behavior, is critical because it differentiates the current theory from its previous model of reasoned action (Ajzen, 1991). Whereas the last two motivational factors, attitudes, and subjective norms, focus on a person's keenness to a particular behavior, perceived behavioral control highlights a person's perceived ease or difficulty in performing the behavior.

Intention

The final construct of the theory of planned behavior is the intention to perform a behavior. Intention refers to the extent to which a person is planning to exert his/her efforts to perform a behavior (Ajzen, 1991). The theory of planned behavior views intention as the best predictor of performance of a behavior. The stronger one's intention to perform a behavior, the more likely one is to perform it. Intentions mediate among the motivational factors (attitudes, subjective norms, and perceived behavior control). Intentions are assumed to express motivational factors and can predict behaviors with considerable accuracy (e.g., Sheppard et al., 1988).

Reviewing the four constructs of the theory of planned behavior reveals the advantages of using this theory in the current study. The theory presents a framework to discern the components of the motivation factors that lead to intention to perform a certain behavior. Therefore, interventions can be designed to target and change the values linked to specific motivation components, resulting in changes in intentions and behaviors. Additionally, the theory helps us to understand the reasons that motivate individuals' intentions to perform. As there are specific components of motivation and intention, we can explain an individual's actions by identifying and estimating his/her beliefs regarding the components. Empirical studies have found that the components of motivation, intentions, and behavioral outcomes tend to differ among different groups (Fishbein et al., 2001). These findings suggest that there may be differences in students' motivation to study math over other subjects, for example according to their immigrant status, which is the interest of the current study.

The Relationship Between School Math Resources and Students' Intentions

School math resources have been considered a critical factor in students' math learning. School math resources extend from material resources to human and cultural resources such as teacher staffing and teacher quality (Adler, 2000). According to Smith, Desimone, & Ueno (2005), human resources have been of interest in educational research since the Coleman Report (Coleman et al., 2004). With regard to human resources, the relationship between teacher characteristics and student achievement has been extensively researched focusing on such topics as assessment results (Ballou, 1996; Ehrenberg & Brewer, 1994, 1995; Ferguson, 1991; Mosteller & Moynihan, 1972); level of content knowledge, mostly indexed by number of courses taken in a subject field (Darling-Hammond, 2000); teachers' years of teaching experience (Murnane & Phillips, 1981; Rivkin et al., 2005); and teachers' levels of participation in content-related professional development opportunities (Cohen & Hill, 2000; Wenglinsky, 2002; Wiley & Yoon, 1995). Interestingly, studies of the association between teacher characteristics and student achievement have shown mixed results.

Teachers are an important factor to increase students' math motivation. Teacher's positive attitudes to students (Lazarides et al., 2018), teacher support for students (Yu & Singh, 2018) and teachers' professional development experiences (Stipek et al., 1998) are positively associated with students' math motivation. These studies showed that the characteristics of teachers are statistically associated with students' math motivation. However, it is unclear whether math teacher staffing and math teacher qualification increases students' math motivation. The previous literature mostly focused on the students' math test scores and their statistical dependency on teacher staffing and teacher qualification (e.g., Chiu & Khoo, 2005) rather than studying students' math motivation. This study drew on the sample of fifteen-year-olds from 41 countries and found that unequal distribution of certified teachers is associated with students' low scores in math, reading, and science. In that sense, it is necessary to shed light on the impact of math teacher staffing and math teacher qualification on the students' math motivation.

Addressing math teacher staffing and math teacher qualification in this study is helpful to inform educational policy directed at math education. U.S. federal K-12 public education policy has designated teacher qualifications as a important factor since the No Children Left Behind Act of 2001. This policy required teachers to be "highly qualified," proxied by full certification, a bachelor's degree, and demonstrated content knowledge (Smith et al., 2005). Though a subsequent federal policy, the Every Student Succeeds Act of 2015 (ESSA), dispensed with the requirement of a bachelor's degree, teacher qualification has remained an important feature in students' success in schooling as well as in state certification and licensure requirements. The findings of the association between math teacher qualification and students' math motivation can guide a policy design.

Math Teacher Staffing

Despite the importance of an adequate supply of qualified teachers, teacher staffing has been a long-standing and controversial issue in the U.S. K-12 education system (Larrabee & Tyack, 1976; Weaver, 1983), especially in math and science (Liu et al., 2008; Murnane & Phillips, 1981; Rivkin et al., 2005). The phenomenon of the shortage of math teachers can be understood in two different ways, as absolute and as relative. In absolute terms, the supply of certified, full-time math teachers is less than the demand. Based on multiple large datasets, Ingersoll and Perda (2009) found that, although national numbers present an overabundance of new teacher candidates, teaching colleges were producing an undersupply of math teachers, which was not sufficient to replace number of math teachers who retired that year. Rahman and colleagues (2017) also pointed out the shortage of in-service certified math teachers. Based on the 2015 National Assessment of Educational Progress, they claimed that shortage of certified math teachers is a universal phenomenon in the U.S. K-12 school system with systematic differences in the percentages of States' shortfalls. They also found that the percentage of eighth-graders taught by state-certified math teachers decreased to 90% from the academic 2014-15 to the academic year of 2012-2013. These studies confirm that there is an insufficient supply of qualified math teachers.

The notion of the relative shortage of math teachers focuses on the low proportion of math teachers among all subject teachers. Colleges underproduce math and science teachers in relation to the high demand in understaffed schools and overproduce teacher candidates with expertise in already well-staffed subjects such as English, social studies, and elementary education (Aragon, 2016). Moreover, based on the national data, Cowan et al. (2016) found that the difficulty in hiring math teachers was persistently observed from 1999 to 2012. Even in years when hiring needed teachers was generally not a challenge (for example, school year 1993-1994), the area of math was in jeopardy. This disproportionate concentration of teacher shortages in math results in an imbalance in students' learning opportunities, as they lack adequate instruction and support in math that they receive in other subjects such as English. Therefore, it appears reasonable to expect students to favor other subjects such as English over math.

Math Teacher Qualification

Since the No Children Left Behind Act of 2001, U.S. federal K-12 public education policy has designated teacher qualifications as a critical factor. Teacher qualifications are a convenient measure to evaluate school quality from a policy perspective as "screening teachers based on qualifications is appealing in its simplicity and is far less demanding than observing teachers in the classroom or measuring teacher attitudes, practices, and beliefs (Huang & Moon 2009, p. 211)." Accurate measurement of teacher qualification's impact on student learning is cost-efficient as it can directly be translated into an education policy surrounding teacher selection and distribution.

The conventional assumption is that teachers who have a bachelor's degree in the academic subject teach students better than teachers without a bachelor's degree. Goldhaber & Brewer (2000) analyzed a nationally representative group of school math and science teachers in the National Education Longitudinal Study of 1988 dataset (NELS). After controlling for individual and family background variables (e.g., sex, race/ethnicity, parental education, family structure, family income, and 10-th grade subject test score), they found that 12th-graders who were taught by teachers who hold a bachelor's degree in math have higher test scores than students who were taught by teachers who do not hold a bachelor's degree. (class size and the percentage of minority students in the class). Rice (2003) also demonstrated the positive effect of teachers who have advanced degrees on their high school students' math achievement.

Contrary to these studies, some studies suggest that teacher qualification does not enhance students' learning. Palardy & Rumberger (2008) analyzed a nationally representative group of elementary school teachers in the Early Childhood Longitudinal Study dataset. Using a hierarchical linear model that disentangles the variance components of child, classroom, and school, this research found that teachers' backgrounds such as advanced degree, years of teaching experience, and certification do not increase students' math achievement. Croninger et al.'s study (2007) provided the similar findings that elementary school teacher's advanced degree has no statistically significant impact on first graders' math achievements. These results show that teacher qualification tends to have no statistically significant impact on students' academic achievement at an elementary school level. These findings are contrary to the positive effect of teacher qualification on high school students' math achievement (Goldhaber & Brewer, 2000). The comparison between the previous studies is not straightforward as the analytic methods, as well as the measures and samples used for each study differ, however, the studies imply that findings related to teacher qualification are inconclusive in the previous studies.

Math Teacher and Student Motivation

Previous studies have found that teachers' attitudes (Lazarides et al., 2018), teachers' support for students (Yu & Singh, 2018), and teachers' professional development (Stipek et al., 1998) are important factors in students' learning motivation. However, there is little research on the relation between mathematics teachers' qualifications and students' mathematics motivation. Most studies have focused on the influence of teachers' qualifications on students' mathematics test scores (e.g., Chiu & Khoo, 2005). However, we know that students' achievement are correlated with their learning motivation (e.g., Amrai et al., 2011). Given this understanding, we could hypothesize that teacher qualification influence not only student achievement but also student motivation. Williams & Williams (2011) found that students get motivated to study harder when they are taught by qualified teachers who represent their teaching abilities (e.g., pedagogical and content knowledge) to students. The authors claimed that "probably the most important factor that educators target to improve students' learning (Williams & Williams, 2011, p.1). This study sheds light on the impact on the availability of certified mathematics teachers on students' mathematics motivation.

In particular, in this study, students' motivation for pursuing mathematics, an area in which there is a critical teacher shortage, is compared with their motivation for studying other subjects such as English, in which there is an ample teacher supply. The rationale of the comparison of the students' motivation by subject is to determine whether school environments that are more favorable to learning mathematics relative to learning English may affect students' motivation in mathematics over other subjects such as English. Such comparisons have rarely been the focus in the literature (Breda & Napp, 2019). For example, Chiu & Khoo (2005) focused only on the absolute values of students' motivations in subjects separately. Drawing on a sample of fifteen-year-olds from 41 countries, they found that unequal distribution of certified teachers was associated with students' low scores in mathematics, reading, and science.

Given that funding and resources are limited in schools, it is reasonable to assume that inequities in resource distribution occur, raising the question of whether a school's relative favoring of mathematics over other subjects influences its students' intention to favor mathematics over other subjects. By pursuing this question, the current study adds to the literature by examining how comparative advantage in school mathematics resources over resources for other subjects influences students' intentions to favor mathematics over other subjects. Based on this review of school mathematics resources and students' mathematics motivation, the first hypothesis of this study is as follows:

Hypothesis 1: School's math resources (Schools that prioritizes school math resources over other subjects) *are positively associated with students' intention (*students' math intention over other subjects).

The Mediating Roles of Attitudes, Subjective Norms, and Perceived Behavioral Control

The constructs of the theory of planned behavior originated in the field of social psychology, which is concerned with the ways in which people's beliefs, feelings, and behaviors are influenced by the actual, imagined, perceived, or implied presence of others in society.

Scholars in a wide range of disciplines have applied the constructs of the theory of planned behaviors to their fields. The majority of the application studies have been conducted in the public health area for such purposes as estimating health-related behaviors, for example intervention for alcohol and drug addiction (Bhochhibhoya & Branscum, 2018) and intervention for eating disorders (Godin & Kok, 1996), followed by other disciplines such as leisure psychology, for example, prediction of leisure intentions and behaviors (Ajzen & Driver, 1992).

In the scholarship of math education, the motivation factors that predict and help interpret an individual's behaviors have been perceived as important (Di Martino & Zan, 2001). Researchers in math education have employed the constructs of the theory of planned behavior to their areas of interest to find differences in the impact of various factors on motivation in a variety of contextual and localized environments, thereby strengthening the theory (Arditzoglou & Crawley III, 1992; Lipnevich et al., 2011; Niepel et al., 2018). Many previous studies have utilized the theory of planned behavior to predict students' math achievement and students' choice of math as a major in college (Arditzoglou & Crawley III, 1992; Burrus & Moore, 2016; Lipnevich et al., 2011; Moore & Burrus, 2019; Niepel et al., 2018). However, no study was found that examined how school math resources influence students' math intentions over other subjects and how the components of the theory of planned behavior (i.e., math pursuit attitudes, subjective norms, perceived behavioral control) mediate this relationship. Guided by the theory of planned behavior, I formulated the second hypothesis to the effect that the three socio-cognitive determinants (i.e., math pursuit attitudes, subjective norms, perceived behavioral control) mediate the relationship between school math resources and students' intentions. The set of hypotheses is presented below. In the following section, I discuss how the theory of planned behavior in math has been applied to the field of education and review those emprical studies that can support the hypothesis. The following subsection serves to introduce a body of literature with regards to (1) math achievement and the theory of planned behavior; and (2) math courses, math careers, and the theory of planned behavior. As the current study focuses on student's intention to pursue a math-related career and take math courses, previous studies that fell into the second category critically influenced for me to design the current study.

Math Achievement and The Theory of Planned Behavior

The constructs of the theory of planned behavior and students' math achievement modeling, which was introduced by Arditzoglou & Crawley III (1992), has produced two strands of research: (a) The use of the constructs of the theory of planned behavior to predict students' grades and (b) The use of the constructs of the theory of planned behavior to predict students' choice of math as their major. The first strand investigates the utility of the theory by estimating its applicability to students' math achievement. Arditzoglou & Crawley III (1992) tested the utility of structural equation modeling to understand the relationships among the constructs of the theory in students' math, science, and life science achievements. Working with a sample of 271 Palestinian female 10th-grade students (90, 90, and 91 students responded to the math, life science, and general science questionnaire, respectively), the researchers first conducted a simple regression analysis and found that the students' achievement intentions were related directly and indirectly to the construct of math attitudes. Also, among the three mediating socio-cognitive determinants (i.e., attitudes, subjective norms, perceived behavioral control), only perceived control in mathematics was directly associated with achievement. Further analysis that incorporated a structural model found that students' mathematics attitudes predicted their achievement intentions. Perceived behavioral control also predicted achievement intentions. Interestingly, achievement intention did not predict students' achievement. This study shows students' intention to achieve a high score on a test, but not necessarily their intention to pursue a math-related career. However, this study's contribution was to provide testing of the measurements and structural parts of the theory of planned behavior. Another downside of this study is that it did not provide accurate numerical values from the report's analysis, preventing precise comparisons with the results of other studies. This study also had a small sample size (90 students), which raises a question about statistical power.

Subsequent studies also investigated the applicability of the theory of planned behavior in predicting students' attitudes toward math by using SEM but with different samples. Working with samples of middle school students in the U.S. (n=382) and Belarus (n=339), Lipnevich et al. (2011) used multivariate analysis to examine the theory's power to predict the role of math attitudes in explaining middle school students' math grades and presented a visual model of the association of their math beliefs and attitudes with their math grades. As data analysis steps, confirmatory factor analyses were fit separately for three socio-cognitive determinants (i.e., math pursuit attitudes, subjective norms, perceived behavioral control) and the intention variables. Then, the study tested two structural models. They found that components of the theory of planned behavior (i.e., attitude, subjective norms, perceived control; and intention) explained between 25% and 32% of the variance in mathematics grades. In line with the theoretical framework of the theory of planned behavior, this research empirically demonstrated that mathematics intentions were determined by three socio-cognitive determinants (attitudes, subjective norms, perceived control) and predicted students' mathematics grades. The three socio-cognitive determinants explained 63% of the variation in intentions. Intention was correlated with attitudes (72%), subjective norms (52%), and perceived behavioral control (65%). All paths to intentions were statistically significant, but the strength of the coefficients varied, the weakest being the coefficient for subjective norms and the most robust the coefficient for attitudes.

Burrus and Moore (2016) replicated and extended Lipnevich et al.'s (2011) study to examine the extent to which the constructs of the theory of planned behavior predict students' math achievement but with a different population, U.S. high school juniors (11th graders) and seniors (12th graders), most of whom had recently taken the ACT math test. The researchers added more independent variables to the model, including high school math grades, number of math courses taken, gender, race/ethnicity, socioeconomic status (i.e., parental income, father's educational level), and conscientiousness. They employed a multiple linear regression model to predict students' ACT math scores by controlling students' background information as follows: Step 1. math course GPA; Step 2. conscientiousness; and Step 3. four components of the theory of planned behavior (i.e., attitudes, subjective norms, perceived control, and intentions). Results showed that the predictive capability of the theory of planned behavior model held for high school students. ACT math scores were positively correlated with math attitudes (r = 0.42**[1]), subjective norms (r = 0.21**), perceived behavioral control (r = 0.29**), and intentions (r = 0.18**). Also, math course GPA was positively correlated with math attitudes (r = 0.39**), subjective norms (r = 0.16**), perceived behavioral control (r = 0.28**), and intentions (r = 0.22**). Among the theory's components, math attitudes presented greater incremental validity in predicting ACT math test scores than student background variables. However, neither perceived behavioral control nor subjective norms statistically significantly predicted ACT math test scores in the model. These findings mostly mirror the findings of Lipnevich et al. (2011). However, Burrus & Moore's study (2016) found that students' math intentions negatively

[1] ** $p < 0.05$

predicted ACT math scores. Note that math intentions that Burrus & Moore (2016) measured denotes a general intention to study mathematics hard (e.g., “I will try to work hard to make sure I learn math.”

Lipnevich et al. (2016) expanded the previous studies by employing the constructs of the theory of planned behavior to estimate variations in student achievement. Cognitive ability (i.e., reasoning ability) and the Big Five personality dimensions (i.e., Extraversion, Neuroticism, Conscientiousness, Agreeableness, and Openness to experience) were added predictors of math grades. The researchers used a hierarchical linear model to investigate the incremental contributions of the constructs of the theory of planned behavior to explaining math grades above and beyond cognitive ability and the Big Five personality dimensions. The sample comprised German college students (n=179) and Belarus college students (n=202), populations that had not been investigated previously. The researchers conducted analyses using structural equation modeling and hierarchical linear modeling for both samples. The hierarchical linear model comprised four steps: Control variables in Step 1, reasoning ability in Step 2, Big Five personality dimensions in Step 3, and the theory of planned behavior in Step 4. Results highlighted that the importance of the components of the theory of planned behavior in predicting math achievement, with math attitudes explaining 21% (Germany) and 7% (Belarus) of variance in math grades over cognitive ability and the Big Five personality dimensions. Among those components, math attitudes yielded a statistically significant beta weight: Germany (.414, $p < .001$), Belarus (.277, $p<.001$). However, for both the German and the Belarus samples, neither intentions, perceived behavioral control, nor subjective norms were statistically associated with students’ math grades.[2] The study results revealed that the amount of variance

[2] As a potential explanation for these unusual results, the authors attributed the time frame of collecting survey data on variables that are part of the theory of planned behavior and students' grades. The authors collected students'

explained by the components of the theory of planned behavior differed between two independent and culturally different samples. Also, it was found that one component can explain math grades substantively more than other components, in this case, math attitudes, which incrementally explained math grades.

Math Courses, Math Careers, and The Theory of Planned Behavior

Above in this section, the second strand of the literature in which the theory of planned behavior was applied focused its use to examine the extent to which the components of the theory can explain students' intention to study math. The studies on this topic covered a wide range of samples and employed different variables, resulting in slightly contrasting results (Foltz et al., 2015; Moore & Burrus, 2019).

Foltz et al. (2015) studied STEM retention, specifically, whether the theory of planned behavior's components apply to the intent to graduate of U.S. students in a freshman chemistry course. The study tested the hypothesis that intention is correlated with the other three components of the theory (attitudes, subjective norms, perceived behavioral control): Subjective norms were statistically associated with intention to remain in the STEM field whereas attitude and perceived behavioral control were not. This finding is different from those of studies showing that math attitudes were a fundamental construct influencing students' pursuit of the STEM field (Lipnevich et al., 2016). The study also found that 16% of the variation in intention to graduate was explained by the model of the theory of planned behavior, implying that the theory of planned behavior explain the intention of students' choice of major. This study offered

grades prior to the survey, potentially resulting in students' math attitudes and other constructs changes due to their grades. The authors suggested future studies would redress this issue (Lipnevich et al., 2016, p. 77). Also, as college students are already a selective sample, the results can be different from a conventional expectation of the relationships of the constructs in this model.

insights that the constructs of the theory of planned behavior can explain students' STEM retention. However, this study had limitations in that the sample was limited to a single group of students at a single university (n=336). Moreover, this study did not control the variables such as socioeconomic backgrounds that may influence the student's STEM retention and the variables of the theory of planned behavior.

Moore & Burrus (2019) augmented previous methodological approaches by including more control variables to measure the impact of the theory of planned behavior on students' intention to major in a STEM field and have a STEM career. The sample comprised 1,958 U.S. high school students (11^{th} and 12^{th} graders), who completed the ACT test and participated in a survey. Results demonstrated that the components of the theory of planned behavior accounted for an 4% and 5% of variance in college STEM major intentions and career intentions, respectively, which was not accounted for by other variables (math course GPA, type of math courses taken, conscientiousness, vocational interests, and student demographic information). Specifically, they found STEM attitudes were the most predictive component. A one-unit increase in math attitudes increased the odds of college STEM major intentions by a factor of 49% (β = 0.40*) and of STEM career intentions by a factor of 57% (β = 0.45*) after controlling for a host of other variables. Math intentions were also a statistically significant predictor of STEM college major intentions (odds ratio = 1.2) but not of STEM career intentions.

Based on the literature outlined I constructed hypotheses regarding the relationships among mathematics pursuit attitudes, subjective norms, and perceived behavioral norms, the underlying beliefs which are posited to make independent contributions to predicting behavior of interest (e.g., Foltz et al., 2015; Moore & Burrus, 2019). The studies found the specific behavioral, normative, or control beliefs most strongly associated with intention and behavior.

For example, Lipnevich et al. (2016) found that attitudes were salient in predicting students' achievement, while Foltz et al. (2015) reported that subjective norms strongly influenced students' choices of major. Identifying the relations of these three constructs to the prediction of intentions has both theoretical and empirical implications. First, the nature of these relations can articulate the theory. In developing the theory of planned behavior, Ajzen (1991) claimed that the relationships to behavior were not accurately identified, even though each of the three components has its own salient behavioral, normative, and control beliefs. In the current study, the hypothesis was formulated to identify the extent to which each of the three socio-cognitive determinants can explain intentions. From an empirical stance, such identification would provide guidance as to which constructs should be targeted for intervention efforts (Montaño & Kasprzyk, 2015). Therefore, the second hypothesis examines each motivation construct's impact on predicting students' intentions to study math over other subjects.

Hypothesis 2. The relationship between a school's mathematics resources and students' intention variables' is mediated by students' motivation variables (math pursuit attitudes; subjective norms, and perceived behavioral control).

Moderating Role of Immigrant Standing in the Relationship Between School Math Resources and Students' Intentions

Immigrant students were reported to experience the persistent inequalities that were reproduced in schooling over time (Hillmert, 2013; Olivos & Mendoza, 2010; Stanton-Salazar & Dornbusch, 1995), though schools were traditionally regarded as the main agent of socialization and integration (Mannion, 2016). Children of immigrants have been historically marginalized and under- supported as they tend to go to schools that lack resources. For example, Schwartz and Stiefel (2004) found that school resources decreased with the representation of students from immigrant families. These relationships were also found to reflect differences in the educational needs of immigrant students due to such factors as poverty, language, and race. It is also plausible that the distribution of school mathematics resources varies within a school so that immigrant students receive fewer benefits than native speakers. Furthermore, these students' mathematics learning can be assumed to differ depending on their particular characteristics, such as their immigration status and type.

This section begins with a host of theories that conceptualize immigrant students' learning in math education to situate my study in the line of the existing studies. Then, I introduce the empirical studies that revealed immigrant students' unique nature in their math motivation and intentions to justify the third hypothesis of this study.

Theory Framing Immigrant Students' Learning in Math Education

The intersection of math and English proficiency has been a critical focus of scholars interested in math education for children of immigrants. Immigrant students tend to use a language other than English at home and bring their language assets to school, creating diversified classroom landscapes. Responding to these, much research in the past two decades, has been motivated by an interest in examining how immigrant students learn math in English (de Araujo et al., 2018). These investigations have been approached from various perspectives, including sociocultural theory and sociopolitical theory (Barwell et al., 2017; de Araujo et al., 2018).

Early researchers who incorporated insights from cognitive theories and psychology treated math learning separately from English language learning or other sociocultural contexts. Researchers grounded in this perspective have investigated the influence of cognitive-process loads on immigrant students' mathematical thinking and performance. Miura et al. (1993)

investigated whether variability in students' math performance can be explained by differences in cognitive representation of language spoken, comparing Asian and non-Asian-language groups. Taking a quasi-experimental approach, Miura et al. (1999) further examined the influence of language characteristics on math thinking and performance. These studies indicated that cognitive representation of number and place value differs depending on the language spoken and influences math influence. One advantage of this theoretical perspective is that it supports analysis of an individual's mental processes to identify effective cognitive learning strategies. However, a drawback is that it does not account for sociocultural contexts, such as those that govern immigrant students' math learning environments.

An alternative approach to examining immigrant students' math learning in relation to their English proficiency is to highlight how their use of English and mathematical performance are linked to sociocultural environments. For this approach, de Araujo et al. (2018) identified two strands of inquiry in math education: sociolinguistic theory (e.g., Khisty & Chval, 2002; Schleppegrell, 2007) and sociocultural theory on learning math (Moschkovich, 2002, 2007, 2013; Razfar, 2012, 2013). From the perspective of sociolinguistic theories of language in math classrooms, there is a specific linguistic register that students have to be familiar with to gain knowledge. The focal interest of this research is to examine how immigrant students, plausibly English language learners, acquire access to the linguistic register in the math classroom (Pimm, 2019). Schleppegrell (2007) pointed out the need to consider linguistic structures in math teaching, such as the multi-semiotic formations and implicit logical relationships. This approach is largely built on a functional linguistics perspective that focuses on linguistics.

Sociocultural theory-based research extended linguists' work to include how students are "being" in math classrooms. Teaching and learning mathematics involves participation in certain mathematics cultural practices (Steele, 2001). The researchers founded on this framework how students understand culturally established mathematical practices in communications with others (e.g., peers and teachers). A third theoretical approach to the investigation of the intersection of math and English learning is based on a sociopolitical perspective (de Araujo et al., 2018). This stance highlights political power dynamics and identity formation (Gutiérrez, 2013). The scholars employing this framework see math as one body of knowledge that transcends language, experience, culture, and power (Kalinec-Craig, 2014). While investigating the educational phenomenon of their interest, they take an equity stance and advocate for social justice by foregrounding the voices of marginalized students and the power dynamics that occur in teaching and learning math (Gutiérrez, 2013; Kalinec-Craig, 2014; Planas & Civil, 2009; Takeuchi, 2018; Turner et al., 2009). Studies of immigrant students' math learning that take this perspective shed light on integrating students' funds of knowledge in school math (Turner & Celedón-Pattichis, 2011), facilitating parents' involvement (Takeuchi, 2018), empowering teachers through professional development (Planas & Civil, 2009). These researchers also explore the knowledge and experiences that are considered personally and socially meaningful to marginalized populations as well as power dynamics in education, with the aim of countering the dominant deficit perspectives on marginalized populations and fostering their active engagement within their contexts.

The three theoretical perspectives reviewed above provide insights useful for finding the missing link in examining the immigrant students' intentions to study math over other subjects, including English. The theory of planned behavior, which is the framework of the current study, is largely based on the cognitive theory introduced in the first place of this section. Though the theory of planned behavior is considered a parsimonious model of behavior prediction, it explains a portion of unaccounted for variance (Hamilton & White, 2012). Ajzen (1991), the developer of the theory of planned behavior, acknowledged that additional predictors might help explain a proportion of unaccounted for variance in the intentions or behaviors. The benefit of the theory is to determine the individual immigrant students' psychological factors; however, it neglects sociocultural factors at play in the immigrant students' intentions. Also, the structural and cultural barriers imposed on immigrant students would result in inequity issues, as highlighted in the sociopolitical view.

As part of an effort to explain the unaccounted for variance in immigrant students' intentions to study math over other subjects, the current study incorporates sociocultural factors and creates a model that expands the theory of planned behavior. School math resources are integrated as a primary predictor in the model, and other demographic factors (i.e., The three individual-level variables: gender; socioeconomic status; and race/ethnicity) are controlled. This expanded model addresses potential differences between immigrant students and non-immigrant students in the distribution of the school resources and impact on math learning. Historically, in the U.S. public education system, immigrant students have access to fewer school resources than non-immigrant children (Chu, 2009; Schwartz & Stiefel, 2004; Smith-davis, 2002). Federal funding has not addressed particular legislation with regards to resources for immigrant students except from the Emergency Immigrant Education Program (EIEP) (Schwartz & Stiefel, 2004). Larger classes and less spending have been documented. Supportive programs such as counseling and parental outreach have been found to be less available to immigrant students than to other students. Some researchers (e.g., Chu, 2009; Schwartz & Stiefel, 2004) have argued that having adequately trained, qualified licensed teachers can help compensate for the lack of other school resources. Thus, access to qualified teachers is incorporated as an important factor related to immigrant students' decision to study math.

Immigrant Students and The Theory of Planned Behavior

Numerous studies have found that culturally different groups show different patterns in the mediating roles of the three socio-cognitive determinants of the theory of planned behavior, with regard to Hispanic-American students (Arditzoglou & Crawley III, 1992), African-American students (Lee, 2012), U.S. students versus Belarus students (Lipnevich et al., 2011), and German students versus Belarus students (Lipnevich et al., 2016). For example, Lipnevich et al. (2016) examined the extent to which the three socio-cognitive determinants explained German college students (n = 179) and Belarus students' (n = 202) mathematics grades. Attitudes showed a statistically significant beta weight for both groups, but the extent to which attitudes were explanatory differed (German sample: B=.414, p <.001; Belarusian sample: B=.277, p <.001). The results demonstrated that even after controlling for cognitive ability and personality, the amount of variance in math grades explained by math attitudes was high for the German sample (16%) and the Belarusian sample (6%) Neither intentions, perceived behavioral control nor subjective norms were statistically related to students' mathematics grades for both samples.

A handful of ethnographies suggest that immigrant students have unique attitudes, subjective norms, and greater perceived behavioral control in school performance than native-born students (e.g., Fuligni, 1997). Despite the unique challenges that immigrant students often face due to socioeconomic background, many immigrant students are in a family/or in peer environment that strongly supports their school performance (Fuligni, 1997). Immigrant parents from diverse countries (e.g., India, Indochina, Central America, Laos, and Vietnam) emphasize their children's academic success (Caplan et al., 1991; Gibson & Ogbu, 1991; Santos, Suarez-Orozco, & Suarez-Orozco, 1995; Waters, 1994). Steinberg et al. (1992) found that immigrant students reported a high level of peer support in academics, which can counterbalance the negative impact of some parenting practices. Positive family and peer involvement has also been reported to crucially encourage immigrant students to pursue the math field (Chachashvili-Bolotin et al., 2019; Onuma et al., 2020).

There are studies that focused on immigrant students with regard to the relation of school math resources to their math intention. Areepattamannil (2012) examined the immigrant students' mathematics and science achievements proxied by their self-concept in each subject. Based on a sample of 1,752 Canadian students who participated in the TIMSS 2007 survey, the study found that immigrant students, both first-generation and second-generation students, showed a positive correlation between positive affect toward mathematics and self-perceived competence in mathematics (0.48 and 0.48, respectively).

Further, the overall multiple regression analysis found that both groups' positive affect toward mathematics and science and self-perceived competence in mathematics and science had statistically significant predictive effects on their mathematics achievement (first-generation immigrant students: R^2=0.36, F (7, 772)=62.03, $p < 0.001$; second-generation immigrant students: R^2=0.42, F (7, 964)=99.72, $p < 0.001$,). Additionally, self-perceived competence in mathematics had a statistically significant positive predictive effect on mathematics achievement for both groups (first-generation immigrant students: B=63.29, $p < 0.001$; second-generation immigrant students: B=60.94, $p < 0.001$). However, positive affect toward mathematics had a statistically significant negative predictive effect on mathematics achievement for both groups (first-generation immigrant students: B=-13.09, $p < 0.001$; second-generation immigrant students: B=-11.25, $p < 0.001$). As shown above, the two groups were quite similar in that the predictors of self-perceived competence in mathematics and positive affect toward mathematics were positively associated with mathematics achievement.

Porche et al. (2016) compared STEM pursuit between immigrant students and non-immigrant students. They found that immigrant students are more likely to pursue a STEM field than U.S.-born peers. They investigated the relationship between immigrant status and the determinants of STEM persistence of 1,073 U.S. high school freshmen and sophomores, 18% of whom were first-generation immigrants to the United States from over 40 different countries. The researchers found that first-generation immigrant students reported statistically higher ratings of aspiration for studying STEM in college or any combination of STEM disciplines than U.S.-born peers. Additionally, first-generation immigrant students had statistically higher levels of both science and mathematics self-concept. This study did not compare first-generation and second-generation immigrant students. Based on these findings, I further postulate the following hypothesis concerning differences between immigrant and non-immigrant students in terms of the three socio-cognitive determinants:

Hypothesis 3: The effect of the school's mathematics resources on student intention will be stronger in the immigrant student group than in the non-immigrant student group.

Summary

Empirical studies have demonstrated how the constructs of the theory of planned behavior play a role in explaining students' math intention. One thing to note is that previous studies defined a student's math intentions differently according to their research interests. In Table 2.1, I list the existing research relevant to how intention has been defined to provide a clear link to the current study. In this study, the long-term math intentions of a sample of middle school students are assessed, highlighting on intentions to (1) take additional math courses over other courses; (2) major in a subject in college that prioritizes math skills over other skills; (3) pursue a career that involves high level math skills.

Table 2.1.

Summary of Studies that Empirically Tested the Theory of Planned Behavior in Math Education Field

Intention	Sample	Method	Results on the relationship of the constructs of TPB (References)
Math achievement intention	U.S. middle school students (n=382) & Belarus student (n=339)	Single-level SEM	Attitudes showed the most positive dependency on intention among three motivational constructs (Lipnevich et al., 2011).
	U.S. middle school students (n=752 from 8 schools)	Longitudinal SEM	All three motivational constructs had a statistically significant association with math achievement intention (Niepel et al., 2018)
	11th and 12th grade U.S. students (n=1,958)	Hierarchical linear regression	Attitudes showed the most positive dependency on intention among three motivational constructs (Burrus & Moore, 2016).
	10th grade Palestinian students (n=271)	Single-level SEM	Both attitude and perceived behavioral control, but not subjective norm influence achievement intention (Arditzoglou & Crawley III, 1992).
	Germany and Belarus college students (n=179, n=202)	Hierarchical linear regression	Only attitudes showed a positive link to math achievement intention (Lipnevich et al., 2016).
STEM majors and careers	11th and 12th grade U.S. students (n=1,958)	Hierarchical logistic regression	Attitude was the only statistically predictive component to choose STEM college majors and STEM careers (Moore & Burrus, 2019).
	U.S college students (n=316)	Single-level SEM	Subjective norms are statistically correlated with the intention to graduate (Foltz et al., 2015).
	9th and 10th U.S. immigrant students (n=1,073)	Mixed-method analysis	Immigrant student reported high self-concept and their high math self-concept was linked to their aspirations for college study in STEM (Porche et al., 2016).

Building on findings in previous studies (Table 2.1), the aim of the current study is to further understanding of students' math intentions. First, data in the second category of Table 2.1. did not represent U.S. middle school students' intentions to pursue STEM majors or careers. The current study fills a gap in the literature by addressing how middle school students are motivated to take more math courses in high school, choose a math major in college, and pursue a math-related career. Second, the current study's methodology is novel in that it employs multiple imputations based on Bayesian estimation to handle missing data, which was not attempted in previous studies, as addressed in Table 2.1. Third, the current study employs a multilevel mediation SEM to reflect the data structure.

Last, the current study revisits the definitions of the constructs of the theory of planned behavior. Previous empirical studies followed a four-factor model (attitudes, subjective norms, perceived behavior, and intention). However, the theoretical rationale of the theory of planned behavior shows that the first two constructs could be more specified, such as subdividing attitudes into experiential attitude and instrumental attitude. This study will fit a commonly used four-factor model along with a six-factor model that reflects more specified definitions of these construct: Math pursuit experiential attitude, math pursuit instrumental attitude, math subjective norms influenced by friends, math subjective norms influenced by parents, perceived behavioral control, and math intention.

CHAPTER THREE

METHODOLOGY

The main purpose of this study is to estimate the effect of school math resources on a student's intention to study math over other subjects in school (e.g., taking more math courses at high school; majoring in math at college; and pursuing a math-intensive career) by considering the mediating roles of socio-cognitive factors (i.e., math pursuit attitudes, subjective norms, perceived behavioral control) and the moderating role of immigrant standing (i.e., immigrant students vs. non-immigrant students). The intent of this analysis is to determine the factors that are associated with students' intentions to study math. In the current study, particular attention is paid to both sociocultural factors (i.e., school math resources) and socio-cognitive factors (i.e., math pursuit attitudes, subjective norms, and perceived behavioral control). This study is also an examination of the effect of a student's immigration status on the relationships among these factors in estimating his/her intentions to study math. To accomplish these aims, the study is guided by the following research questions: (1) How does a school that prioritizes resources for school math over other subjects (regressors $\boldsymbol{x}$) influence students' exhibiting intentions to pursue math over other subjects (outcome $\boldsymbol{y}$)?; (2) Is the resulting effect mediated by students' math pursuit attitudes, subjective norms, perceived behavioral control (mediators $\boldsymbol{m}$); (3) Is it associated with students' immigrant standing (moderator $\boldsymbol{z}$)?"

To address the first two research questions, I apply a proposed 2-1-1 multilevel mediation SEM model in which only two observed independent variables (x_i) are measured at level 2 (Fang, Wen, & Hau, 2019; Preacher, Zhang, & Zyphu, 2011; Preacher, Zyphur, & Zhang, 2010). The data are composed of two hierarchical levels, in which I represents the number of the first level units (schools), and J the number of subjects (students) within a unit (school): School's math resource variables (x_{ij}), Student's intention variables (y_{ij}), Student's immigration variables (z_{ij}), and Student's motivation variables (m_{ij}). Multilevel SEM was used for its unique benefits for the PISA dataset, which can produce more accurate estimates than a single-level approach to hierarchical data structure that decomposes a school-level effect and student-level effect. I also took a two-step approach that involves first analyzing a measurement model for a latent construct and then analyzing a structural model in accordance with Anderson & Gerbing (1988). The goals of the analysis are to evaluate the estimated effects based on the research hypotheses, investigate patterns of effects within a set of variables (e.g., school math resources, math pursuit attitudes). Then, to address a third research question, I investigated the group differences with respect to estimated effects. Measurement invariance was tested, and then a structural model was tested. One limitation in this multiple group analysis was that it had to be run at a single level due to our data's small cluster size. Detailed information was provided later in the analytic process part.

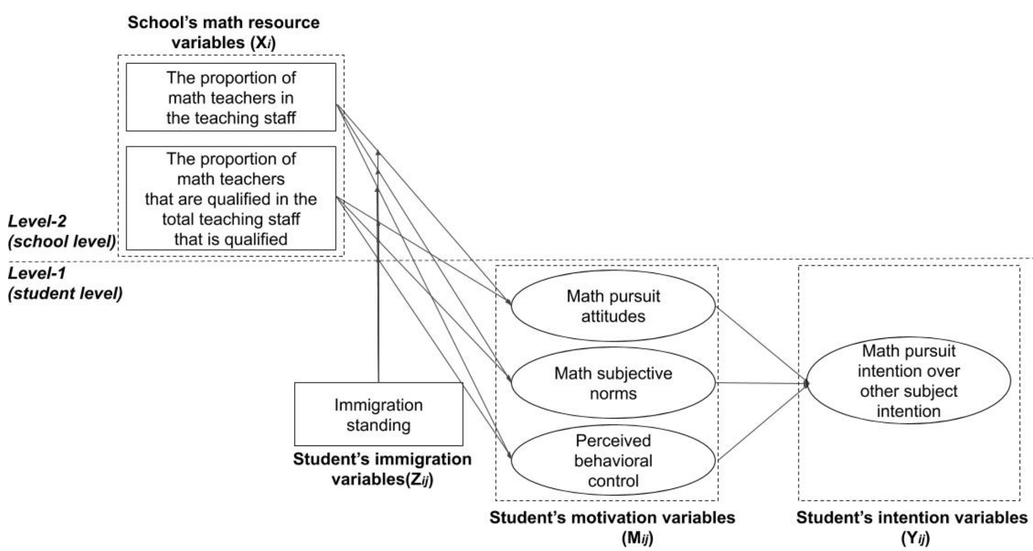
Details of the research methodology employed in the current study are presented in this chapter as follows: (a) research model, (b) Multilevel Mediation Structural Equation Modeling and Multiple Group Analysis, (c) instruments, and (d) procedures and data analysis. The first section presents the research design. The second section provides a brief introduction to mediation, moderation, and moderated mediation in the context of models for hierarchical data structures. The third section provides information on the sample, variables, sampling, and selection bias. Then, the fourth section offers a missing data handling strategy that this study took, which was a predictive mean matching technique based on a Bayesian framework. The last section describes details about procedures and data analysis.

Research Model

The research model for this study is presented in Figure 3.1. This baseline theoretical model was formed based on the theories and previous studies discussed in Chapter 2. The research model is based on the premise that school math resources influence a student's intention to study math. The relationship between these constructs is hypothesized to be mediated by three socio-cognitive factors (i.e., math pursuit attitudes, subjective norms, and perceived behavioral control). Additionally, the research model includes the moderating effects of group standing (i.e., immigrant students versus non-immigrant students) on the variables. The direct effect of school math resources on intention to pursue math over other subjects is omitted from Figure 3.1. For the sake of clarity, control variables are not presented in this research model: Gender, socioeconomic status, and race/ethnicity.

Figure 3.1

Overview of the Research Model



Note. Each rectangle refers to an observed variable and each oval to a latent variable. For the sake of clarity, direct effects, confounding variables, and differences between in-group and between-group of the mediating effects are excluded in this figure.

The research model posits the hypothesis linked to each factor in this model. The first hypothesis refers to the relationship between the independent variable (x_i) of this research and the dependent variable (y_{ij}).

Hypothesis 1. School's math resources (degree to which schools that prioritize school math resources over other subjects) are positively associated with students' intention (*students' math intention over other subjects).*

The second hypothesis is related to the mediating roles of socio-cognitive determinants (m_{ij}) in the linkage of school math resource variables (x_i) and students' math intention variables (y_{ij}).

Hypothesis 2. The relationship between a school's mathematics resource variables and students' intention variables' is mediated by students' motivation variables.

The third hypothesis deals with the group difference (immigrant students vs. non-immigrant students) (z_{ij}) in the relationship of the factors in the current study.

Hypothesis 3. The effect of the school's mathematics resources on student intention will be stronger in the immigrant student group than in the non-immigrant student group.

Multilevel Mediation Structural Equation Modeling and Multiple Group Analysis

The current study employs a multilevel mediation structural equation modeling and multiple-group mediation structural equation modeling. To preface the discussion of multilevel moderated mediation, in this section, I define basic concepts associated with Multilevel Structural Equation Modeling. Then, I describe the concepts related to mediation, moderation, and moderated mediation in an SEM framework. Finally, I describe the use of multilevel moderated mediation SEM. This section was built on developments presented in previous methodological studies (Depaoli & Clifton, 2015; Fang et al., 2019; Rusá et al., 2018; Wang & Preacher, 2015; Zyphur et al., 2019).

Mediation at a Single Level and at Multiple Levels

Mediation occurs when the effect of an independent variable (*x*) on a dependent variable (*y*) is transmitted by a mediator (*m*) (Preacher et al., 2007). Mediation analysis examines the means by which *x* exerts its effect on Y (See Figure 3.2). Figure 3.3 depicts a path diagram of the mediation model. The mediation effect is quantified as the product of the two regression coefficients a_{mx} and b_{ym}. a_{mx}. This product denotes to the unstandardized slope coefficient of m regressed on *x*. b_{ym} and c'_{yx} refers to the conditional coefficients of *y* regressed on *m* and *x*, respectively (Wang & Preacher, 2015). This mediation effect model can be written as a regression equation:

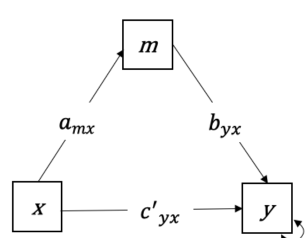
$$m_i = v_m + a_{mx}x_i + \varepsilon_{m,i} \quad (1.1)$$

$$y_i = v_y + b_{ym}m_i + c'_{yx}x_i + \varepsilon_{y,i}, \quad (1.2)$$

wherein v_m and v_y represents intercept and $\varepsilon_{m,i}$ and $\varepsilon_{y,i}$ represents a regression residual. The two regression coefficients a_{mx} and b_{ym} represent the indirect effect of *x* on *y* via *m*. In a classic theory, researchers typically test for mediation by examining whether $a_{mx}b_{ym} \neq 0$.

Figure 3.2

Path diagram of a mediation model (Zyphur et al., 2019, p. 475)



Equations 1.1 and 1.2 represent a mediation effect at a single level. As Preacher et al. (2010) point out, the use of single-level mediation is inappropriate for multilevel data structures because "the assumption of independence of observations is violated when clustered data are used, leading to downwardly biased standard errors if ordinary regression is used" (p. 209). In the multilevel model, observed variables reflect between- and within-group parts when data are nested (Zyphur et al., 2018, p. 483). In turn, the mediation model in Equations 1.1 and 1.2 can be re-formulated by decomposing the between-components and within-components of relevant variables (For simplicity, I omit random slopes).

$$m_{Bj} = v_{Bm} + a_{Bmx}x_{Bj} + \varepsilon_{Bm,j} \tag{1.3}$$

$$y_{Bj} = v_{By} + b_{Bym}m_{Bj} + c'_{Byx}x_{Bj} + \varepsilon_{By,j} \tag{1.4}$$

$$m_{Wij} = a_{Wmx}x_{Wij} + \varepsilon_{Wm,ij} \tag{1.5}$$

$$y_{Wij} = b_{Wym}m_{Wij} + c'_{Wyx}x_{Wij} + \varepsilon_{Wy,ij}, \tag{1.6}$$

wherein a *B* subscript refers to a between-group component (i.e., a school mean) and a *W* subscript refers to a within-group component (i.e., a student's relative standing after subtracting the school mean). To test for mediation, researchers will typically check the indirect effects being $a_{Bmx}b_{Bym}$ (between-group) and $a_{Wym}b_{Wym}$ (within-group), respectively.

Previous empirical studies have tested mediation models in various settings, depending on the level at which independent variable x, mediator m, and dependent variable y are measured. The most frequently used multilevel mediation model is found to be a 2-1-1 model with an independent variable at level 2, a mediator at level 1, and a dependent variable at level 1. This so-called upper level mediation is prevalent in educational and organizational studies, in which researchers tend to look for treatment effects on an individuals' outcomes (e.g., Hom et al., 2009;

Zhang, Zyphur, & Preacher, 2009). A group-level treatment is hypothesized to impact a person-level outcome through a person-level mediator.

The current study also employs a 2-1-1 model to examine how school resources (x_j, level 2) affect students' math intentions over other subjects (y_{ij}, level 1) via students' math motivation (m_{ij}, level 1). The school resources variable is a between-level predictor of only between-level variability in students' math intentions over other subjects. Thus, what matters is not simply to measure whether students' math motivation mediates the relationship between the school resources variable and the student math intention variables, but also whether, and to what extent, between-level variability in student math motivation serves as a mediator of the cluster-level effect of school resources on the between-level component of math intentions.

Moderation at a Single Level and at Multiple Levels

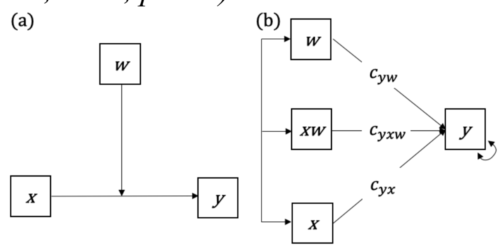
Moderation (*z*) is said to occur when the strength of the relationship between two variables is dependent on a third variable. According to Preacher et al. (2007), the third variable, called a moderation variable, "interacts with *x* in predicting *y* if the regression weight of *y* on *x* varies as a function of *z* (p. 186)." *z* could be a continuous variable or categorical variable. A simple moderation is expressed as an equation form (Zyphur et al., 2019):

$$y_i = v_y + c_{yx}x_i + c_{yz}z_i + c_{yxz}x_iz_i + \varepsilon_{y,i}, \quad (2.1)$$

wherein i is a unit of observation; v is an intercept; c is a regression coefficient; and ε is a residual. The conditional effect, $c_{yxz}x_iz_i$, is that x's effect on y differs across the levels of z. In a classic theory, researchers typically test for moderation by estimating a confidence interval around c_{yxz}. Figure 3.3. represents (a) a conceptual diagram of a moderation model and (b) a path diagram of a moderation model, wherein covariances among predictors are accounted for when deriving coefficients rather than explicitly estimated.

Figure 3.3

Moderation model (Zyphur et al., 2019, p. 475)



Multilevel moderation implies the same extension to both the between group and within group cases as discussed in the section of multilevel mediation. The equation for multilevel moderation would be as follows (for concision, I omit random slopes, again):

$$y_{Bj} = v_{By} + c_{Byx}x_{Bj} + c_{Byz}z_{Bj} + c_{Byxz}x_{Bj}z_{Bj} + \varepsilon_{By,j} \quad (2.2)$$

$$y_{Wij} = c_{Wyx}x_{Wij} + c_{\mathrm{Wyz}}z_{Wij} + + c_{Wyxz}x_{Wij}z_{Wij} + \varepsilon_{Wy,ij}, \quad (2.3)$$

where moderation has a similar form except that *B* parts indicate groups and the *W* parts indicate individuals. The *B* coefficients can be utilized to make inferences about groups. The *W* coefficients can be utilized to make inferences about individuals. *B* and *W* moderation effects will be defined by examining c_{Byxz} and c_{Wyxz}.

Moderated Mediation at a Single Level and a Multiple Levels

Moderated mediation occurs when the strength of a mediation effect is conditional on the level of a moderator variable. James et al. (1984) explained moderated mediation assessment as involving relations that required the addition of a moderator, either the $\hat{m} = f(x)$ or the $\hat{y} = f(m)$ relations, or both (p. 314). Generally, this method entails first demonstrating an interaction effect of an independent variable (*x*) and a mediator (*m*) on a dependent variable (*y*), then showing a moderator (z) of that effect. Moderated mediation is different from mediated moderation. The mediated moderation method probes the interaction effect of an independent variable (x) and a moderator (z) on a mediator (m) and on a dependent variable (y) separately. In other words, mediated moderation does not demand the examination of conditional indirect effects (Preacher et al., 2007, p. 193). Because the conditional effect of students' immigrant standing is of interest in this study, a moderated mediation approach is taken. This study tests the mediational model, an independent variable (x) -> a mediator (m) -> dependent variable (y) in separate groups, where an immigrant (=1), otherwise non-immigrant (=0). The third hypothesis of the current study is a moderated mediation hypothesis and it is examined with the multiple group SEM analysis.

Figure 3.4 provides a diagram of a single-level moderated mediation model. Figure 3.4 includes (a) a conceptual diagram of our single-level moderated mediation model; and (b) a path diagram of the single-level moderated mediation model, wherein predictor covariances are explicitly estimated, including a covariance among m and mw. Path coefficients are given with a terms referring to initial paths in a mediation effects equation, b terms indicating second paths in a mediation effects equation, and c' paths indicating direct effects. The equation of this model can be formulated as follows (Zyphur et al., 2019):

$$m_i = v_m + a_{mx}x_i + a_{mz}z_i + a_{mxz}x_iz_i + \varepsilon_{m,i} \tag{3.1}$$

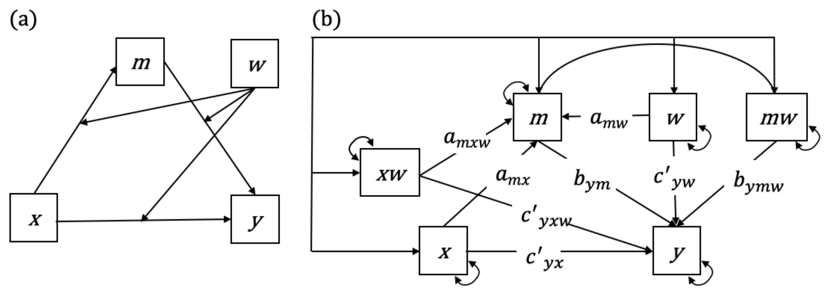
$$y_i = v_y + b_{ym}m_i + b_{ymz}m_iz_i + c'_{yx}x_i + c'_{yz}z_i + c'_{yxz}x_iz_i + \varepsilon_{y,i}, \tag{3.2}$$

wherein z moderates the effect of x on m and m on y. z moderates the direct effect of x on y. The moderation coefficients are a_{mxz} and b_{ymz}, both of which are multiplied by z. As shown in Figure 3.3 (Moderation model), a_{mxz} enables moderation of the path linking the independent variable (x) and the mediator (m). b_{ymz} enables moderation of the path linking the mediator (m)

and dependent variable (y). Note that b_{ym} is part of the mediation effects that involve paths a_{mx} and a_{mxz}, and these paths can be moderated by z when multiplied by b_{ymz}.

Figure 3.4

Moderated Mediation Model (Zyphur et al., 2019, p. 476)



Note. (a) A conceptual diagram of our single-level moderated mediation model; (b) A path diagram of our single-level moderated mediation model, wherein predictor covariances are explicitly estimated, including a covariance among m and mw.
Path coefficients are labeled as in our equations, with a terms indicating initial paths in a mediation effects equation, b terms indicating second paths in a mediation effects equation, and c' paths indicating direct effects.

Moderated mediation model in a multilevel framework has the same extension to the between-group (B) and the within-group (W) case. Equations 3.1 and 3.2 can be reformulated as follows:

$$m_{Bj} = v_{Bm} + a_{Bmx}x_{Bj} + a_{Bmz}z_{Bj} + a_{Bmxz}x_{Bj}z_{Bj} + \varepsilon_{Bm,j} \tag{3.3}$$

$$y_{Bj} = v_{By} + b_{Bym}m_{Bj} + b_{Bymz}m_{Bj}z_{Bj} + c'_{Byx}x_{Bj} + c'_{Byz}z_{Bj} + c'_{Byxz}x_{Bj}z_{Bj} + \varepsilon_{By,j} \tag{3.4}$$

$$m_{Wij} = a_{Wmx}x_{Wij} + a_{wmz}z_{Wij} + a_{Wmxz}x_{Wij}z_{Wij} + \varepsilon_{Wm,ij} \tag{3.5}$$

$$y_{Wij} = b_{Wym}m_{Wij} + b_{Wymz}m_{Wij}z_{Wij} + c'_{Wyx}x_{Wij}$$
$$+ c'_{Wyz}z_{Wij} + c'_{Wyxz}x_{Wij}z_{Wij} + \varepsilon_{Wy,ij}, \tag{3.6}$$

wherein all terms are as before (Equations 3.1, and 3.2), but the B parts apply to groups and the W parts apply to individuals. The same logic of moderated mediation exists, with B indirect effects for groups as $(a_{Bmx} + a_{Bmxz}z_{Bj})(b_{Bym} + b_{Bymz}z_{Bj})$ and B direct effects for groups as $(c'_{Byx} + c'_{Byxz}z_{Bj})$. W indirect and direct effects for individuals are indicated as $(a_{Wmx} + a_{Wmxz}z_{Wij})(b_{Wym} + b_{Bymz}z_{Wij})$ and $(c'_{Wyx} + c'_{Wyxz}z_{Wij})$, respectively.

Multilevel Structural Equation Model Specification

Multilevel Structural Equation Modeling (MSEM) is a combined set of the features of multilevel modeling (MLM) and structural equation modeling (SEM), which extends conventional latent variable modeling to accommodate a hierarchical data structure (Depaoli & Clifton, 2015, p. 327). MLM offers a framework for the analysis of multilevel data structure that have parameters that vary at more than one level. It accounts for variations in parameter values due to the sampling of units at more than one level, such as individuals who are nested within aggregate units (Raudenbush & Bryk, 1992; Snijders & Bosker, 1999). SEM offers a framework for testing hypothesis about relationships of the variables to make inferences about unobservable latent constructs from observed variables. SEM accounts for error in the measurement of constructs in multivariate data by modeling parameter values such as means and covariances (Bollen, 1989). The combination of MLM and SEM allows the measurement of variances of variables by partitioning the variance of variables in nested data: W components and B components. In this study, the following questions were built following (Depaoli & Clifton, 2015).

$$y_{ij} = \mu + y_{Wij} + y_{Bj} \quad (4.1)$$

In Equation 4.1, y_{ij} is a vector of observation i in cluster j where the B components y_{Bj} and the W components y_{Wij} are independent; μ indicates the grand means. The item responses y_{ij} are conditionally normally distributed with group means μ_j (i.e., random intercepts) and covariance matrix $\sum_{W.}$ – The random effects μ_j are normally distributed with expected value μ and covariance matrix $\sum_{B.}$

For observed ordinal response variables, it is assumed that the category choice is derived from normally distributed continuous latent response variable ${y^*}_{ij}$. A vector of unknown thresholds denoted by $\alpha_j = (\alpha_1, \ldots, \alpha_k)^{\mathrm{T}}$ is assumed to exist, such that:

$$y_{ij} = k, \quad \text{iff } \alpha_k < {y^*}_{ij} < \alpha_{k+1}, \quad k = 0, \ldots, K, \tag{4.2}$$

with $-\infty = \alpha_0 < \alpha_1 < \ldots < \alpha_k < \alpha_{k+1} = \infty$. For dichotomous indicators, latent response variable is ${y^*}_{ij} = 1$ if $y_{ij} > 0$ and ${y^*}_{ij} = 0$ otherwise.

Like conventional SEM, MSEM consists of a separate measurement model and structural model, but each model can be split into the *B* components and the *W* components. Measurement models are models that relate observed indicators to the latent constructs. Structural models indicate how the latent constructs relate to each other. The measurement model and the structural model at the within-group level have the following forms:

$$\mathrm{y}_{ij} = \mu_j + \Lambda_W \eta_{Wij} + \varepsilon_{Wij} \tag{4.3}$$

$$\eta_{Wij} = \beta_W \eta_{Wij} + \zeta_{Wij} \tag{4.4}$$

Equation 4.3, the measurement model for the W component, includes Λ_W, a factor loading matrix that is multiplied by a vector of a unit-level latent variable η_{Wij} that includes the latent variable and the latent covariate; ε_{Wij} denotes a vector of *W* residuals. The structural model for the W component, Equation 4.4 includes the term β_W, indicating a matrix of structural coefficients; η_{Wij}, indicating a vector of unit-level latent variables; and ζ_{Wij}, indicating a factor of errors distributed as multivariate normal. In other words, W structural model is in β_W. To estimate W moderated mediation parameters, β_W needs to be examined.

The measurement model and the structural model for the between-group component are respectively denoted as:

$$\mu_j = \mu + \Lambda_B \eta_{Bj} + \varepsilon_{Bj} \tag{4.5}$$

$$\eta_B = \beta_B \eta_{Bj} + \zeta_{Bj} \tag{4.6}$$

Λ_B, η_{Bj}, ε_{Bj}, β_B, and ζ_{Bj} are the terms for B components corresponding to the within-group terms Λ_W, η_{Wij}, ε_{Wij}, β_W, and ζ_{Wij}. In other words, the B structural model is in β. To estimate B moderated mediation parameters, β needs a particular examination.

Instruments

This section illustrates the sample used for this study and identifies the measures used for testing the measurement model and the structural model of the present study.

Sample

This study's sample stemmed from two datasets of the 2012 *Programme for International Student Assessment (PISA)*: The U.S. 2012 PISA Student Questionnaire and the U.S. 2012 PISA School Questionnaire. Initially, approximately 4,978 US students from 162 schools completed the 2012 PISA background questionnaire. I will decrease selection bias by including students whose parents had only one option in their selection of schools for their children (item SC04 of the U.S. PISA 2012 School Questionnaire): Which of the following statements best describes the schooling available to students in your location? The three answer options were granted to survey respondents. This dissertation only included survey respondents who selected option (3):

(1) There are two or more other schools in this area that compete for our students; (2) There is one other school in this area that competes for our students; and (3) There are no other schools in this area that compete for our students. Then, the set of samples included a total of 1,108 students from 36 schools with 90% non-immigrant students (n=1,004) and 10% immigrant students (n=104).

Measures

The independent variables related to school resources (x_j) that I use are at the school level, namely a. the proportion of mathematics teachers in the total teaching staff and b. the proportion of qualified math teachers in the total qualified teaching staff. The latent outcome variable (y_{ij}), students' math pursuit intentions over other subjects, is estimated by five binary items. Three latent mediators (m_{ij}) include math pursuit attitudes (eight ordinal observed indicators), subjective norms (six ordinal observed indicators) and third, perceived behavioral control (six ordinal observed indicators). The effect of a single moderator (z_{ij}), immigrant standing, is measured after being categorized into immigrant student group and non-immigrant student group. I include possibly confounding variables at the school level (c_i) and the student level (c_{ij}) in the model. A detailed description of the variables used in the analysis can be found in Part 3, Variables list.

Independent Variable: School's math resource variables

The U.S. 2012 PISA school questionnaire provides information on school resources particularly devoted to math. I derive two variables to measure the levels of school resources dedicated to math relative to other subjects. These variables aggregate part-time and full-time teachers by computing the total number of teachers in each relevant group as the sum of full-time teachers and one-half times the number of part-time teachers. I adapted the computation of the school's relative resources of math over other subjects from Breda & Napp (2019)'s article.

- The proportion of math teachers in the teaching staff
  - SC09Q11 "No. of teachers - Total Full-Time"
  - SC09Q12 "No. of teachers - Total Part-Time"
  - SC10Q11 "No. of math teachers - Total Full-Time"
  - SC10Q12 "No. of math teachers - Total Part-time"
- The proportion of math teachers that are qualified in the total teaching staff that is qualified
  - SC09Q31 "No. of teachers - at least Bachelors Qualified Full-Time"
  - SC09Q32 "No. of teachers - at least Bachelors Qualified Part-Time"
  - SC10Q61 "No. of math teachers - BA/BS or MA/MS Qual Full-Time"
  - SC10Q62 "No. of math teachers - BA/BS or MA/MS Qual Part-Time"
  - SC10Q21 "No. of math teachers - BA/BS or MA/MS Qual Math Major Full-Time"
  - SC10Q22 "No. of math teachers - BA/BS or MA/MS Qual Math Major Part-Time"

Dependent variable: Student's intention variables

Math pursuit intention over intentions in other subjects is measured using five items from the U.S. 2012 PISA Student Questionnaire: ST48Q01 to ST48Q05. Specifically, students reported their intentions to use math in their future studies and careers through five forced-choice format items: "Please darken only one of the following two circles. All items were reverse-coded for a higher score to reflect higher math intention (math intention =1, otherwise 0).

- Taking math courses
  - ST48Q01 "(1) I intend to take additional math courses after I finish high school. (2) I intend to take additional English courses after I finish high school."
  - ST48Q04 "(1) I plan on taking as many math classes as I can during my education. (2) I plan on taking as many science classes as I can during my education."
- Math as college major and future careers

- ST48Q02 “ (1) I plan on majoring in a subject in college that requires math skills. (2) I plan on majoring in a subject in college that requires science skills.”
- ST48Q05 “(1) I am planning on pursuing a career that involves a lot of math. (2) I am planning on pursuing a career that involves a lot of science.”

Mediating variable

The U.S. 2012 PISA student questionnaire asked students to report their math motivation. A mediating variable consists of three variables of socio-cognitive determinants (e.g., math pursuit attitudes, subjective norms, perceived behavioral control) derived from the theory of planned behavior and one socio-environmental factor (i.e., school math resources). The items are responded using a four-point scale from strongly disagree (=4) to strongly agree (=1). I reverse-coded some items to indicate a higher score corresponds to higher attitudes, subjective norms, and perceived behavioral control.

Math Pursuit Attitudes. Two types of attitudes are relevant to math pursuit attitudes: Experiential attitude and instrumental attitude (Fishbein & Ajzen, 2010; Moore & Burrus, 2019): Experiential attitude involves a perception of a person who considers math or doing math as enjoyable and pleasant. This type of attitude counts a person’s intrinsic value as a motivation for his/her certain behavior. Instrumental attitude involves a perception of a person who thinks math or doing math has a utility cost. Students who have an instrumental attitude find it useful and worthwhile to study math. The variables used to estimate experiential attitudes and instrumental attitudes are shown as follows (The variable name of the construct: ST29 from the U.S. 2012 PISA Student Questionnaire):

- ST29Q01 “I enjoy reading about math.”
- ST29Q03 “I look forward to my math lessons.”
- ST29Q04 “I do math because I enjoy it.”
- ST29Q06 “I am interested in the things I learn in math.”

- ST29Q02 “Making an effort in math is worth it because it will help me in the work that I want to do later on.”
- ST29Q05 “Learning math is worthwhile for me because it will improve my career prospects.”
- ST29Q07 “Math is an important subject for me because I need it for what I want to study later on.”
- ST29Q08 “I will learn many things in math that will help me get a job.”

For the Math pursuit attitude variables, students answered on a four-point scale with the following categories: Strongly agree (=1), Agree(=2), Disagree(=3), and Strongly disagree(=4). The Math pursuit attitude variables are reverse-coded so that a higher experiential attitude and instrumental attitude correspond to a higher level of attitudes on all items.

Subjective Norms. Subjective norm denotes a person’s perceived social pressure to perform a given behavior. According to Fishbein & Ajzen (2010), subjective norms include two dimensions: Injunctive norms and descriptive norms. Injunctive norms refer to a perceived rule that should be followed. It involves a perception of to what extent other people would approve or disapprove of a given behavior (Zou & Savani, 2019). For example, students who have parents who oblige them to study math are more likely to take a math course over other courses. Descriptive norms refer to perceived behaviors that are usually performed by other people. The descriptive norms are built on observations of what people around a person do. For instance, students who are surrounded by friends who do well in math predict their likelihood of taking a math course over other courses. The 2012 U.S. PISA Student dataset has six items related to subjective norms that capture only descriptive norms. These six items reflect parents’ influence and friends’ influence to perform math, with three items relevant to friends’ influences, and three items linked to parents’ influences (The variable name of the construct: ST35 the U.S. 2012 PISA Student Questionnaire):

- ST35Q01 “Most of my friends do well in math.”
- ST35Q02 “Most of my friends work hard at math.”
- ST35Q03 “My friends enjoy taking math tests.”
- ST35Q04 “My parents believe it’s important for me to study math.”
- ST35Q05 “My parents believe that math is important for my career.”
- ST35Q06 “My parents like math.”

For the Subjective norm variables, students answered on a four-point scale with the following categories: Strongly agree(=1, Agree(=2), Disagree(=3), and Strongly disagree(=4). These variables are reverse-coded so that a higher ST35 corresponds to a higher level of social norms on all items.

Perceived Behavioral Control. Perceived behavioral control denotes the extent to which a person perceives his/her capability to perform control over behavior performance (Ajzen & Icek Ajzen, 2006). Students who have high perceived behavioral control over math are those students who believe that doing math is within their control. The U.S. 2012 PISA Student Questionnaire provided six items related to perceived behavior control over math (The variable name of the construct: ST43 the U.S. 2012 PISA Student Questionnaire):

- ST43Q01 “If I put in enough effort, I can succeed in math.”
- ST43Q02 “Whether or not I do well in math is completely up to me.”
- ST43Q03 “Family demands or other problems prevent me from putting a lot of time into my math work.”
- ST43Q04 “If I had different teachers, I would try harder in math.”
- ST43Q05 “If I wanted to, I could do well in math.”
- ST43Q06 “I do badly in math whether or not I study for my exams.”

To indicate that a higher point of the items of the Perceived behavioral control construct corresponds to a higher level of the perceived behavioral control, the three variables of

ST43Q01, ST43Q02, and ST43Q05 were reverse-coded. The other three variables, ST43Q03, ST43Q04, and ST43Q06, kept their initial coding results as these items used the negative wording that reversed the response scale.

Moderating Variable

The U.S. 2012 PISA student questionnaire asked students to report the country of origin of themselves, their mother and father (ST20Q01; ST20Q02; ST20Q03): "In what country were you and your parents born? Please darken only one circle in each column. (See Table 1)" I derived a variable that categorizes a student into an immigrant or non-immigrant student.

Table 3.1

The Item Used for Building a Moderating Variable

	You	Mother	Father
United States	O	O	O
Other country	O	O	O

Controlled variable

The control variables are included.

- Gender: ST04Q01 "(1) Female, (2) Male"
- Socioeconomic status: ST13N01 "Mother's highest schooling; ST17N01 Father's highest schooling."
- Race/ethnicity: RACETHC "White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander."

Bayesian Estimation to Handling Missing Observations

Handling missing data is crucial to avoid substantial sampling and measurement bias. The PISA 2012 assessment design has a rotation design that produces a vast amount of missing data by design. In this study, a Bayesian imputation method, using multiple imputation by chained equation (MICE), was employed to precisely impute missing values. The specific technique used was predictive mean matching. This matching method is known for producing imputed values quite similar to “real” values. I ran the predictive mean matching estimation via the *R* package Multivariate Imputation by Chained Equations (MICE). As von Davier (2013) suggested, I also set this chained method to start with only observed variables while excluding plausible values (i.e., test scores). Below, I provide a brief introduction of the Bayesian framework to help readers understand predictive mean matching. Next, more detailed information about the PISA 2012 Questionnaire design is addressed, followed by an overview of the predictive mean matching method with its diagnostics. Last, I present the process and multiple imputation results of the current study.

Bayesian Estimation

The Bayesian framework originated over 250 years ago in Bayes’ introduction of a method to take prior beliefs into account in data analysis (van de Schoot et al., 2017). Conceptually, Bayesian inference is simple. Bayes’ theorem provides a mechanism for including one’s knowledge about a theory with data and generating the probability of a theory given the data (Baldwin & Fellingham, 2013, p.153).

$$p(\text{theory}|\text{data}) = \frac{p(\text{data}|\text{theory})\, p(\text{theory})}{p(\text{data})}, \tag{4.7}$$

wherein p(theory|data) is known as the posterior distribution; p(data|theory) refers to the probability of the data given a theory (typically known as the likelihood); p(theory) indicates the probability of the theory prior to the data (known as the prior); and p(data) is the probability of the data. In other words, the Bayesian approach assumes that prior knowledge (i.e., theory) about parameter values (e.g., mean and standard deviation) in a descriptive model may exist. These parameter values have some prior credibility that can be informative but also uncertain. The Bayesian method reallocates credibility to these parameter values consistent with their prior assumptions and the data. This reallocated credibility formalizes the posterior distribution over these parameter values.

Speaking colloquially, as Kruschke & Vanpaemel (2015, p. 279) pointed out, this process of formalization is quite similar to the logic of the detective Sherlock Holmes: "When a person has eliminated the impossible, then whatever remains, no matter how improbable, must be the truth (Doyle, 1890)." Sherlock Holmes has low credible initial knowledge. Then, he gathers evidence based on that prior knowledge. Finally, he reallocates credibility to the possibilities remaining after impossibilities are eliminated. All inferences follow from Bayes' theorem. Essential in Bayesian estimation is finding the most credible parameter values for the model by looking at how uncertainty changes when new data are considered. In sum, Bayesian analysis has "a distribution of credibility over the space of parameter values (p. 280)" that can provide enormous flexibility in designing models.

Bayesian estimation provides various advantages that the classical frequentist approach cannot deliver. Key is that a researcher can interpret parameter uncertainty represented by posterior distribution (Kruschke & Vanpaemel, 2015). Bayesian intervals (i.e., credible intervals) treat their bounds as fixed and the parameter as a random variable. In this sense, the interpretable answers would be like the true parameter having a probability of 0.95 of falling into a 95% credible interval. It is different from the conventional frequentist interpretation of parameters, which uses confidence intervals derived from sampling distributions. Intervals' bounds are treated as random variables and the population parameter as fixed. The interpretable answers would be something like, "we are 95% confident that the population parameter is between lower bound *x* and upper bound *y*." The frequentist approach demands constructing sampling distributions from the auxiliary null hypothesis along with p-value and deviation statistics to determine whether or not an estimated parameter value is statistically significant (Kruschke & Vanpaemel, 2015, p. 281). The limitation of a frequentist approach is that, even though it can find a maximum-likelihood estimate (MLE) of parameter values in a multilevel non-linear model, the subsequent task of interpreting the MLE's uncertainty is daunting. Bayesian estimation does not construct sampling distributions from the auxiliary null hypothesis, and it can provide a clear view of parameter uncertainty when a researcher has prior knowledge about the joint distribution of parameters. Researchers need to take steps to compare multiple models in a Bayesian approach to get some evidence about whether the model (e.g., SEM) best represents the data-generating mechanisms. Bayesian methods will inform the explanatory powers of the models based on the posterior odds ratio approach unlike a frequentist model selection approach. Bayesian analysis offers a convenient setting for a wide range of complicated models such as multilevel settings (SAS, 2017). Based on this understanding, I chose a Bayesian multiple imputation for the analysis of the dataset from the U.S. PISA 2012 Questionnaire.

The PISA 2012 Assessment Design

PISA 2012 introduced a rotation design for the Student Context Questionnaire to ensure extensive coverage of student context questions while minimizing student burden and fatigue caused by excessive survey length. A rotation design, which is also commonly called a matrix sampling design, uses item packages distributed over a number of different booklets (OECD, 2012). The design consists of Forms A, B, and C. The forms include a systematic combination of clusters of items. Each form has a common part and a rotating part. The rotating part consists of two rotated clusters of items, thereby overlapping one of the clusters between the two rotated forms. In other words, one-third of the items in the dataset have missing values by design. Students are randomly allocated to one of the three forms.

Table 3.2. presents a matrix sampling design of PISA 2012 Student Context Questionnaire. The common part includes commonly used demographic variables such as student's age, parents' occupation, and immigrant status. The current study's moderating variable (i.e., immigrant status) and control variables (e.g., gender) are included in this common part. Cluster 1 includes math motivation variables (i.e., math pursuit attitudes (ST29), subjective norms (ST35), perceived behavioral control (ST43)) and math intention variables (i.e., mathematics intentions (ST48)), which corresponds to the current study's mediators and dependent variable, respectively. Note that Form C does not have Cluster 1, which requires a certain approach to deal with missing data.

Table 3.2.

PISA Student Questionnaire Matrix Sampling Design (Kaplan & Su, 2016; OECD, 2012)

Form A	Form B	Form C
Common part	Common part	Common part
Cluster 1	Cluster 1	Cluster 1 missing
Cluster 2	Cluster 2 missing	Cluster 2
Cluster 3 missing	Cluster 3	Cluster 3

Note. For detailed information for each item refer to Table 6.3 and Table 6.4 in the PISA 2012 assessment and analytical framework (OECD, 2012, pp. 193-194).

In handling missing data, it is necessary to classify missing data problems based on the likelihood of the data being missing (Donald B. Rubin, 1976): Missing completely at random (MCAR); Missing at random (MAR), and Missing not at random (MNAR). MCAR denotes that the probability of being missing is the same for all cases. MAR means that the chance of being missing is the same only within groups defined by the observed data. MAR is more common than MCAR. MNAR indicates that being missingness depends not only on observed data but also on unobserved data. Though the PISA 2012 Student Questionnaire is designed to have missing values for one-third of its items in any form, the use of listwise deletion in handling data is not recommended. Because listwise deletion can not only reduce the statistical power of the tests but also lead to bias in the results. A multiple imputation method can generate unbiased results under MCAR or MAR (Enders, 2010; Little & Rubin, 2019). PISA has a large number of variables. As long as mass imputation of covariates is employed, there can be an equal amount of bias in the estimates of relationships with other variables (Fetter, 2001).

Predictive mean matching

Definitions

Multiple imputation for missing data is drawn from the Bayesian framework. The Bayesian approach treats missing values as unobserved random variables, which have a distribution depending on the observed variables (Rubin, 1987, 2004). Multiple imputation by chained equations (MICE), which employs a univariate regression model consistent with the scale of the variable with missing data, is widely used in statistical analyses. Observed data are treated as predictors for missing values. Kaplan and Su (2016) used the data from the PISA 2012 Student Context Questionnaire to show which multiple imputations reproduce the marginal distributions of the data most accurately. In this study, three algorithms were used: first, predictive mean matching for all items; second, Bayesian linear regression under the normal model for continuous items; and third, proportional odds logistic regression for categorical variables. Empirical evidence was found that predictive mean matching produced the densities of imputed values that were closest to those of the observed values. Drawn on this study, I chose predictive mean matching as an imputation method in the current study.

Predictive mean matching can be defined as following (Kaplan & Su, 2016, p. 59; Vink et al., 2014, p. 65). Let X_{obs} be the predictors with observed data and let X_{miss} be the predictors with missing data on the target variable *y*.

1. Use linear regression of Y_{obs} given X_{obs} to estimate $\hat{\beta}$, $\hat{\sigma}$, and $\hat{\varepsilon}$ by means of ordinary least squares.
2. Draw σ^{2*} as $\sigma^{2*} = \hat{\varepsilon}^T \hat{\varepsilon} \,/\, A$, where A is a χ^2 variate with $n_{obs} - r$ degrees of freedom.
3. Draw β^* from a multivariate normal distribution centered at $\hat{\beta}$ with covariance matrix $\sigma^{2*}\,({X^T}_{obs}\,X_{obs})^{-1}$.
4. Calculate $\hat{Y}_{obs} = X_{obs}\,\hat{\beta}$ and $\hat{Y}_{mis} = X_{mis}\,\beta^*$.
5. For each $\hat{Y}_{mis,i}$, find $\Delta = |\,\hat{Y}_{obs} - \hat{Y}_{mis,i}|$.
6. Randomly sample one value from $(\Delta^{(1)}, \Delta^{(2)}, \Delta^{(3)})$, where $\Delta^{(1)}$, $\Delta^{(2)}$, and $\Delta^{(3)}$ are the three smallest elements in Δ, respectively, and take the corresponding $Y_{obs.i}$ as the imputation.
7. Repeat steps 1-6 *m* times, each time saving the completed dataset.

In the current study, all observed variables in the student questionnaire were used for multiple imputations using *pmm* in the *R* package MICE, including the common part and clusters. Multiple imputation was performed five times (*m* = 5), which is the standard number in most of the multiple imputation studies.

Diagnostics

The validity of the imputed data was assessed according to the criteria set by Rässler (2002) and procedures suggested by Kaplan and Su (2016). Rässler (2002) identified four levels of imputation validity: First, preserving individual values; second, preserving joint distributions;

third, preserving correlation/covariance structure; and fourth, preserving marginal distributions. In the current study, the third and fourth levels were checked to meet the minimum requirement.

To assess how well the imputed data reproduce the original marginal distributions, I created plots of item densities that displayed imputed data values and original data values by item. The two density distributions in a plot were expected to be close to each other under the assumption of MCAR. Figure 3.5. presents the kernel density plots for four items, each representing one construct of the theory of planned behavior (math pursuit attitudes; math subjective norms, perceived behavior; and math intention). I created these plots using a predictive mean matching technique under five imputations in the R program. The density plots present that the density estimates of the imputed and observed data have no stark discrepancies. This finding can be interpreted as indicating that the distributions match up well, and imputed data can be used for further analysis instead of observed data with missing values.

I performed one more check on distributional discrepancies by examining the correlations between imputed values and the values in the original dataset, as recommended by Rässler's 2002) third level of imputation validity. Table 3.3 displays the computed correlations among four items within each rotated form. As these four items were included only in Form A and Form B, I provided the correlation values corresponding to these two forms. Table 3.3 shows that each correlation of two items of the imputed values is similar to that of the observed values. In other words, the correlations are well-preserved in the imputed datasets when a predictive mean matching method under five imputations is used. The results of both the kernel density plots and the correlation estimation suggest that multiple imputations appropriately reproduced the observed values. Thus, it was justifiable to use imputed data to proceed with confirmatory factor analysis and structural modeling.

Figure 3.5

Kernel Density Plots of Imputed and Observed Values for Item ST29Q07, ST35Q06, ST43Q06, and ST48Q02 Using Predictive Mean Matching (pmm) under Five Imputations

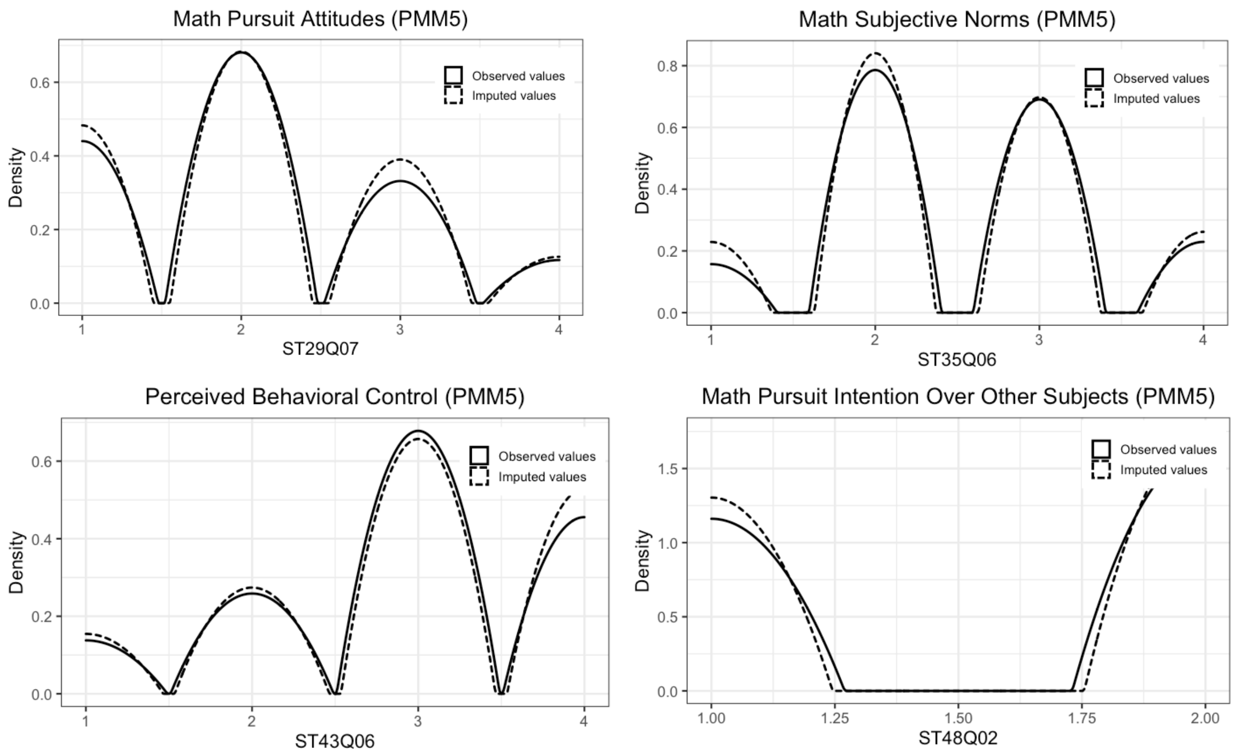


Table 3.3

Correlations among Items ST29Q07, ST35Q04, ST43Q06, and ST48Q04 within Each Booklet Using pmm under Five Imputations

	ST29Q07 with ST35Q06	ST29Q07 with ST43Q06	ST29Q07 with ST48Q02	ST35Q06 with ST43Q06	ST35Q06 with ST48Q02	ST43Q06 with ST48Q02
Form A	0.35 (0.36)	0.30 (0.30)	0.21 (0.21)	0.05 (0.06)	0.12 (0.13)	0.12 (0.13)
Form B	0.26 (0.27)	0.23 (0.23)	0.17 (0.18)	0.01 (0.01)	0.14 (0.12)	0.10 (0.10)

Note. Each cell contains a correlation values from imputed values and observed values.

Estimates in the bracket () denote a correlation value from observed data.

Analytic Methods

I applied a proposed 2-1-1 multilevel mediation SEM model in which only two observed independent variables ($\boldsymbol{X_i}$) are measured at level 2. In analyzing data, I used *R* statistical software. The primary package that I used for the SEM model was the *lavaan* package that was specifically developed for latent variable analyses (More information: https://lavaan.ugent.be/). The SEM for this study consisted of three steps. As Anderson & Gerbing, (1988) suggested, a measurement model was first tested to evaluate its reliability and validity. For a measurement model, confirmatory factor analysis (CFA) was applied to test whether measures of a latent variable are consistent with the theory of planned behavior. Then, a path model was tested with the observed and latent variables evaluated via the measurement model. In the analysis of a path model, the model for the total sample was first fitted. Then, I tested the measurement invariance across an immigrant student group and non-immigrant student group to compare their path models further. After these two groups interpreted a given set of items in a conceptually similar manner, I performed a multigroup path model analysis that compared an immigrant student group's path model to a non-immigrant student group's one. The following section describes each step in more detail: (a) Measurement Model; (b) Measurement Invariance Test; (c) Structural Model.

Measurement Model

CFA presumes that researchers know how the latent structure of the studied measures would look, such as the number of factors and what manifest variables are related to which latent variable. The CFA tests the unidimensionality, reliability, and validity of each latent variable. The unidimensionality test of the CFA precedes the reliability and validity tests. Each observed variable in the measurement model is expected to be sufficiently unidimensional to one latent variable. As a latent variable is not directly observed, at least three observed variables are required to define one latent variable. Each observed variable is expected to have a factor loading of 0.6 or greater. Whether a measurement model is fit or not is determined by various model fit indices. Conventionally, three fitness categories are used to examine the model fit, as shown in Table 3.4: Absolute fit, incremental fit, and parsimonious fit. This table also introduces a set of widely-used fit indices corresponding to each category (e.g., Root Mean Square Error of Approximation, RMSEA). In this study, at least one fit index per category was used to determine the model fit as recommended by Hair et al. (2010).

Table 3.4

Level of Acceptance to the Goodness-of-fit Indices

Category	Model fit indices	Reference values	References
Absolute fit	Chisq (Discrepancy Chi Square)	p-value > 0.05	Wheaton et al. (1977)
	RMSEA (Root Mean Square of Error Approximation)	RMSEA < 0.08	Browne & Cudeck (1992)
	SRMR (Standardized Root Mean Squared Residual)	SRMR < 0.08	Hu & Bentler (1999)
	GFI (Goodness of Fit Index)	GFI > 0.9	Jöreskog & Sörbom (1986)
Incremental fit	CFI (Comparative Fit Index)	CFI > 0.9	Bentler (1990)
	TLI (Tucker-Lewis Index)	TLI > 0.9	Bentler & Bonett (1980)
Parsimonious fit	Chisq/df (Chi Square/Degrees of Freedom)	Chisq/df < 0.3	Marsh & Hocevar (1985)

In the current study, it was assumed that the data could be appropriate for a four-factor model (i.e., math pursuit attitudes, math subjective norms, perceived behavioral control, and math intention) or a six-factor model (i.e., math pursuit *experiential* attitudes, math pursuit *instrumental* attitudes, math subjective norms influenced *by friends*, math subjective norms influenced *by parents,* perceived behavioral control, and math intention). Although the four factor model had usually been tested in previous studies, I assumed that the six factor model could have a better model fit considering what each construct meant. For example, my friends' influence on me is different from my parents' influence. I first fit the four-factor model and then compare the model fit with the fit of the six-factor model. The six-factor model showed a better model fit than the four-factor model, as shown in Table 3.5. Given the theoretical definition and the results of the empirical testing, I deemed the six-factor model as more appropriate to fit the data. Therefore, I performed further analysis with the six-factor model.

Table 3.5

The Model Fit of a Four-factor Model #1 and a Six-factor Model #2

	A four-factor model #1	A six-factor model #2
The number of items	24 items	24 items
The model fit indices	χ^2 (*df* = 246.00) = 2917.29 (p < .001), RMSEA: 0.10; SRMR: 0.11, GFI: 0.78, CFI: 0.68, TLI: 0.64	χ^2 (*df* = 237,00) = 1343.41 (p < .001), RMSEA: 0.07; SRMR: 0.07, GFI: 0.91, CFI: 0.87, TLI: 0.84

As shown in Table 3.5., the model fit for the six-factor model does not meet the recommended requirements for a good model. If their default models have a poor fit, researchers commonly revise them by considering the factor loading and modification index. The observed variables that have factor loadings of less than 0.6, can be removed one by one beginning with the lowest factor loading until the model has a good fit (Kwahk, 2019, p. 5). If the model fit is still not acceptable after eliminating the items with low factor loadings, a follow-up approach is to check the modification index (i.e., LaGrange Multiplier), which is an estimate of the amount of the chi-square value that would be decreased if a single parameter restriction is eliminated from the model (MacCallum et al., 1992).[3] The use of the modification index helps to identify what changes can improve model fit (e.g., highlighting residual correlations). A downside of this approach is the risk of overfitting the model too closely to a given dataset. For this reason, a revised model should be carefully developed.

In the current study, I carefully revised the default model (i.e., six-factor model with 24 items) while acknowledging the pros and cons of using the modification index. Initially, the default measurement model had 24 items. Then, I revised a model for it to have 21 items because the construct of perceived behavior control showed low validity and reliability values. This construct (i.e., perceived behavior control) had three negatively-worded items and three positively-worded items, and the difference in wording seemed to hinder internal reliability. I removed the three negatively-worded items (ST43Q03, ST43Q04 & ST43Q06) with the result that the model fit indices improved and indicated a better fit, as shown in Table 3.5.

As shown in Table 3.6., besides the chi-square value, the other model fit indices indicated that the revised model had an acceptable fit. Not all items showed factor loading values greater than 0.6, suggesting that removal of more items could be considered. However, to keep at least three items per latent variable, I retained the remaining 21 items. Though the model fit was not ideal due to an unsatisfactory chi-square value, the other indices corresponding to a category of "absolute fit" (i.e., RMSEA, standardized root mean residual (SRMR), and the goodness of fit indices (GFI)) showed a good fit. The ANOVA test results showed that the model fit of the revised model was statistically significantly better than the fit of the first model (χ^2 difference = 466.95, *df* difference = 63, $p < 0.001$).

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[3] I also studied the concept of modification index on this website. https://centerstat.org/what-are-modification-indices-and-should-i-use-them-when-fitting-sems-to-my-own-data/

Table 3.6

The Model fit of a Six-factor Model #2 and a Six-factor Model #3

	A six-factor model #2	A six-factor model #3
The number of items	24 items	21 items *Note.* 3 items were removed (ST43Q03, ST43Q04 & ST43Q06)
The model fit indices	χ^2 (*df* = 237.00) = 1343.41 (p < .01), RMSEA: 0.07; SRMR: 0.07, GFI: 0.91, CFI: 0.87, TLI: 0.84	χ^2 (*df* = 167,00) = 791.77 (p < .01), RMSEA: 0.06; SRMR: 0.06, GFI: 0.94, CFI: 0.92, TLI: 0.90

Reliability and Validity

After ensuring the unidimensionality of the model, I checked whether the scales were reliable and presented construct validity. Reliability is a measure of the consistency of a latent variable across corresponding items. Three criteria were used for evaluating reliability: first, Cronbach's coefficient (α), a measure of internal consistency; second, composite reliability (CR); and average variance extracted (AVE):

$$\text{Cronbach's } \alpha = \frac{n\bar{c}}{\bar{v}+(n-1)\bar{c}}, \tag{5.1}$$

wherein n refers to the number of items, $\bar{c}$ is the average inter-item covariance among the items and $\bar{v}$ denotes the average variance. The reasonable threshold for Cronbach's α can be anywhere from 0.7 and up (Nunnally & Bernstein, 1994).

$$\text{CR} = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} v(\varepsilon_i)}, \tag{5.2}$$

wherein λ_i refers to standardized loading for the *i*th item, $v(\varepsilon_i)$ equals to the variance of the error term for the *i*th item and n refers to the number of items. The acceptable value of CR is equal to or greater than 0.7 (Bagozzi & Yi, 1988).

$$\text{AVE} = \frac{\sum_{i=1}^{n} \lambda_i}{\sum_{i=1}^{n} \lambda_i{}^2 + \sum_{i=1}^{n} v(\varepsilon_i)}, \tag{5.3}$$

wherein λ_i refers to standardized loading for the ith item, $v(\varepsilon_i)$ equals to the variance of the error term for the ith item and n refers to the number of items. The reasonable value of AVE equals to 0.5 or above 0.5 (Fornell & Larcker, 1981).

Construct validity is commonly evaluated by using the concepts of convergent validity and discriminant validity. Convergent validity refers to the extent to which the items of a latent variable that theoretically should be related are in reality related. Convergent validity is considered good when the items under one latent variable have high intercorrelations and high factor loadings. Convergent validity is also evaluated using the Average Variance Extracted (AVE) value. An AVE value higher than 0.5 meets the threshold of a good convergent validity. Discriminant validity is established when the items that should not be related theoretically are not in fact related. The AVE value is also often used to evaluate discriminant validity. If the positive square root of the AVE for each latent variable should be greater than the squared correlation involving the latent variables (Fornell & Larcker, 1981).

The analysis of the reliability coefficients for the revised model with 21 items revealed that the fifth latent variable, Math subjective norms influenced by parents, did not establish sufficient evidence of acceptable reliability and validity (Table 3.7). One item under that latent variable , "My parents like math (ST35Q06)," had a low factor loading, which decreased the reliability and validity value. I removed this item and re-ran the analysis with the remaining 20 items. The analysis of the reliability and validity values of model #4 with the 20 items showed overall acceptable values.

As the number of the items (n=20) had been finalized, I re-ran the CFA on model #4, the final model. Table 3.8 presents the model fits of this model. The ANOVA test revealed that the revised model and final model were statistically different from each other (χ^2 difference = 35.42, *df* difference = 6, $p < 0.001$). I set model #4 as a final measurement model for a single-level CFA. In the finding section, I reported the details of the factor loadings, reliability values, and correlation values of this final model for a single-level CFA. Additionally, I also fit a multilevel CFA and provide the multilevel CFA results in the finding section.

Table 3.7

Reliability Values of the Six-factor Model #3 (21 items) and the Six-factor Model #4 (20 items)

Latent Variable	Cronbach's α		CR		AVE	
	Model #3	Model #4	Model #3	Model #4	Model #3	Model #4
1 Math pursuit experiential attitudes	0.85	0.85	0.85	0.85	0.59	0.59
2 Math pursuit instrumental attitudes	0.83	0.83	0.83	0.83	0.55	0.55
3 Math subjective norms influenced by friends	0.69	0.69	0.71	0.71	0.46	0.46
4 Math subjective norms influenced by parents	**0.55**	**0.68**	**0.60**	**0.71**	**0.36**	**0.59**
5 Perceived behavioral control	0.68	0.68	0.69	0.69	0.41	0.41
6 Math pursuit intention over other subjects	0.74	0.74	0.76	0.76	0.46	0.46

Note. Model #3=A six-factor model with 21 items, Model #4=A six-factor model with 20 items

Table 3.8

The Model Fits of the Six-factor Model #2, #3, and #4

	A six-factor model #2	A six-factor model #3	A six-factor model #4
The number of items	24 items	21 items * 3 items were removed (ST43Q03, ST43Q04 & ST43Q06)	20 items *One more item were removed (ST35Q06)
The model fit indices	χ^2 (*df* = 237.00) = 1343.41 ($p < .01$), RMSEA: 0.07; SRMR: 0.07, GFI: 0.91, CFI: 0.87, TLI: 0.84	χ^2 (*df* = 167.00) = 791.77 ($p < .01$), RMSEA: 0.06; SRMR: 0.06, GFI: 0.94, CFI: 0.92, TLI: 0.90	χ^2 (*df* = 168.00) = 841.04 ($p < .01$), RMSEA: 0.06; SRMR: 0.07, GFI: 0.93, CFI: 0.91, TLI: 0.89

Measurement Invariance Test

The analysis of measurement invariance of latent constructs was run as a part of multigroup confirmatory factor analysis. This measurement invariance test evaluates whether survey responders from different groups interpret the same items in a similar way or not. For a comparison of groups to be valid, measurement invariance should be ensured. If it is not ensured, it means that groups responded differently to the measures and consequently, it is invalid to compare the groups on that factor (van de Schoot et al., 2012, p. 3). The test of measurement invariance involves setting cross-group constraints on parameters such as factor loadings, intercepts, and residual variances. Testing was conducted step-by-step by comparing hierarchically more constrained with less constrained models (Davidov et al. 2014; Vandenberg & Lance, 2000 cited by Cieciuch et al., 2019), as shown in Table 3.9: (a) configural invariance; (b) weak/loading invariance; (c) strong/scalar invariance, and; (d) strict invariance. After testing the measurement model's invariance, I provided the results in the finding section by providing the model results (e.g., factor loadings) and the model fit of each model.

Table 3.9

Tests for Measurement Invariance (Xu, 2012, p. 8)

	Measurement invariance test	Constrained parameters	Free parameters	Comparison model
1	Configural invariance	FMean (= 0)	fl+inter+res+var	
2	Weak/metric invariance	fl+Fmean (= 0)	inter+res+var	Configural invariance
3	Strong/scalar invariance	fl+inter	res+var+Fmean*	Weak/loading invariance
4	Strict in invariance	fl+inter+res	Fmean*+var	Strong/scalar invariance

Note. fl = factor loadings, inter = item intercepts, res = item residual variances, Fmean = mean of latent variable, var = variance of latent variable, Fmean is fixed to 0 in group 1 and estimated in the other group.

Structural Model

The structural model was used to test the three hypotheses of the current study. The SEM results included the structural path and estimates at each level of the model. First, I verified the path model for the total sample. Then, I tested the multigroup SEM model. The first model for the total sample was measured with a multilevel framework (i.e., school level and student level). However, the multigroup path model was measured at a single level due to the small cluster size of the immigrant student group, 104 immigrant students from 21 schools in the dataset, with a mean value of 5. When a multigroup path model was estimated at a multilevel, the *R* software announced a warning message that some variables had no variations. Thereby, despite the multilevel data structure, the multigroup path model analysis had to be estimated at a single level. To check group differences, I conducted an ANOVA test between the model that freely estimated all parameters and the model that constrained all parameters equally across the groups.

CHAPTER FOUR

RESULTS

Considering the following three research questions, this chapter presents the results of the procedures and analysis described in Chapter 3. The research questions are presented with information about the questionnaire examined and the hypotheses applied. Then subsequently the results presented, which is followed by a summary of the results for the three central research questions.

1. How does a school that prioritizes resources for school math over other subjects (regressors *x*) influence students' exhibiting intentions to pursue math over other subjects (outcome *y*)?
2. Is the resulting effect mediated by students' math pursuit attitudes, subjective norms, perceived behavioral control (mediators *m*)?
3. Does this effect change with students' immigrant standing (moderator *z*)?"

First, in this study, the latent structure of six latent variables and corresponding observed variables in data drawn from the 2012 U.S. PISA School Questionnaire and Student Context Questionnaire was examined. The measurement model was performed at both a single level and at a multilevel (i.e., students located at level 1 were nested within schools located at level 2). Although a structural model for the total sample was fit to a multilevel framework, due to small cluster size, a multiple group structural model had to be fit to a single-level framework. The results of both measurement models showed the presence of six latent variable structures with a reasonable model fit. The structural model for the total sample also presented a good fit. The structural model indicated that a school's math variables did not influence students' intentions to pursue math over other subjects in the long term (Hypothesis 1). There was also no mediation effect of students' math pursuit attitudes, subjective norms, and perceived behavioral control (Hypothesis 2). The multigroup analysis of the structural model revealed that an immigrant student group and non-immigrant student group differed from one another in relationships among some variables (Hypothesis 3). The following section provides details of the results with figures and tables.

Measurement Model

Single Level Measurement Model

A set of CFAs was conducted to test the model for the total sample, comprising an immigrant student group and non-immigrant student group. I tested a six-factor confirmatory factor analysis model with 20 items: (1) math pursuit experiential attitudes, (2) math pursuit instrumental attitudes, (3) math subjective norms influenced by friends, (4) math subjective norms influenced by parents, (5) perceived behavioral control, and (6) math pursuit intention over other subjects.

The fit of the six-factor model for the total sample is presented in Table 4.1. Most of the fit statistics used for model evaluation indicated that this model had an acceptable fit: The RMSEA (0.06) was equivalent to a good fit. The SRMR value was 0.07. GFI (0.93), CFI (0.91) and TLI (0.89) showed a reasonable fit as well. However, the Chi-square/df value was greater than 3 (χ^2 = 841.04, degree of freedom (*df*) = 168, p < .01), which indicated a poor fit. These conflicting results are not rare in applied research because it is harder to achieve a good fit with the chi-square value than the CFI and TLI values (Cieciuch et al., 2019). Additionally, I provide the factor loadings of each item, showing that 45% of the items (n=9/20) had factor loadings above 0.6. The factor loading values of two constructs' measures (i.e., perceived behavioral control and math intention over other subjects) were found to be relatively lower than the factor loadings for the other constructs.

Next, I analyzed the CFA model separately for an immigrant student group and non-immigrant student group. The model for the non-immigrant student group fitted the data well while the immigrant student group's model did not show the relatively good fit, as presented in Table 4.1. This result appeared plausible given that the sample size of the immigrant student group (n=104) was substantively smaller than that of the non-immigrant student group (n=1,104). An immigrant student group's model fit indices and factor loadings are presented in Table 4.1 as well: χ^2 (*df* = 168) = 276.59 p < .01, RMSEA = 0.08, SRMR = 0.08, GFI = 0.82, CFI =0.86, TLI: 0.82. The model for the non-immigrant student group showed a good fit: χ^2= 798.65, *df* = 168, p < .01, RMSEA = 0.06, SRMR = 0.07, GFI = 0.93, CFI = 0.91, and TLI 0.89. For comparison, I provided these two groups' factor loadings and z-values in Table 4.1 along with those values for the total sample.

Table 4.1

Items, Standardized Loadings, and z values of the Four-factor Measurement Model

Latent Variable Name Scaled Item	Total sample		Immigrant student group		Non-immigrant student group	
	λ_x	z	λ_x	z	λ_x	z
Math pursuit experiential attitudes						
I enjoy reading about math.	0.63	25.71	0.68	8.78	0.62	24.28
I look forward to my math lessons.	0.71	29.51	0.63	8.90	0.71	28.10
I do math because I enjoy it.	0.77	31.49	0.81	10.89	0.76	29.67
I am interested in the things I learn in math.	0.67	27.34	0.57	8.05	0.68	26.27
Math pursuit instrumental attitudes						
Making an effort in math is worth it because it will help me in the work that I want to do later on.	0.61	26.39	0.38	4.91	0.63	26.13
Learning math is worthwhile for me because it will improve my career prospects.	0.64	28.09	0.62	8.28	0.64	26.72

Latent Variable Name Scaled Item	Total sample		Immigrant student group		Non-immigrant student group	
	λ_x	z	λ_x	z	λ_x	z
Math is an important subject for me because I need it for what I want to study later on.	0.70	28.96	0.69	10.02	0.70	27.37
I will learn many things in math that will help me get a job.	0.56	23.19	0.51	6.43	0.57	22.58
Math subjective norms influenced by friends						
Most of my friends do well in math.	0.58	21.58	0.47	6.69	0.59	20.83
Most of my friends work hard at math.	0.61	21.51	0.68	8.30	0.60	20.11
My friends enjoy taking math tests.	0.34	13.63	0.50	6.26	0.33	12.44
Math subjective norms influenced by parents						
My parents believe it's important for me to study math.	0.41	16.60	0.29	3.51	0.42	16.28
My parents believe that math is important for my career.	0.70	22.08	0.93	5.37	0.68	21.22
Perceived behavioral control						
If I put in enough effort, I can succeed in math.	0.47	22.04	0.53	6.74	0.47	20.97
Whether or not I do well in math is completely up to me.	0.48	18.44	0.44	5.40	0.49	17.68
If I wanted to, I could do well in math.	0.47	17.81	0.43	4.96	0.47	17.12
Math pursuit intention over other subjects.						
I intend to take additional math courses over English courses after I finish high school.	0.19	11.92	0.19	3.90	0.19	11.25
I plan on taking as many math classes as I can during my education over science classes.	0.40	28.21	0.43	9.84	0.40	26.37
I plan on majoring in a subject in college that requires math skills over science skills.	0.32	21.62	0.22	4.58	0.33	21.38
I am planning on pursuing a career that involves a lot of math over science.	0.40	27.84	0.45	10.31	0.39	26.21

Goodness of fit

	RMSEA	SRMR	GFI	CFI	TLI
Total sample model χ^2 (*df* = 168) = 841.04 (p < .01)	0.06	0.07	0.93	0.91	0.89
Immigrant student group χ^2 (*df* = 168) = 276.59 (p < .01)	0.08	0.08	0.82	0.86	0.82
Non-immigrant student group χ^2 (*df* = 168) = 798.65 (p < .01)	0.06	0.07	0.93	0.91	0.89

Note. z = Z value, *df* = degree of freedom, RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; CFI = comparative fit index; TLI = Tucker-Lewis index

Composite Reliability (Single Level)

Table 4.2 shows the composite reliability, descriptive statistics, and correlations for the six latent variables along with other variables used for a structural model (e.g., control variable). The reliability analysis found that all the latent variables had acceptable reliability values, similar to or greater than 0.70 (Nunnally & Bernstein, 1994).

Math pursuit experiential attitudes had the reliability value (α = 0.85), followed by math pursuit instrumental attitudes (α = 0.83), math subjective norms influenced by friends (α = 0.71), math subjective norms influenced by parents (α = 0.71), perceived behavioral control (α = 0.69), and math pursuit intention over other subjects (α = 0.76). The mean scores of the mediators of the current study ranged between 2.27 to 3.23, which is closer to the value of "agree (=3)." Standard deviations for the mediators are ranged from 0.37 to 0.75. The mean score of the dependent variable (i.e., math pursuit intention over other subjects) was 0.5 on a scale of preferring math over other subjects (=1) and preferring other subjects over math (=1). The correlation coefficients for the latent variables are ranged from 0.06 to 0.46, which showed the weak or moderate associations between the latent variables.

Table 4.2

Composite Reliability, Descriptive Statistics, and Correlations for the Latent Variables

	Variable name	1	2	3	4	5	6	7	8	9	10	11
1	[C] Gender	-										
2	[C] SES	0.04	-									
3	[C] Race	0.00	-0.19***	-								
4	[I] MR1	0.00	-0.08**	0.09**	-							
5	[I] MR2	-0.02	0.05	0.00	-0.18***	-						
6	[M] MPA1	-0.02	0.01	-0.01	-0.01	0.02	-					
7	[M] MPA2	-0.04	0.04	-0.03	0.00	0.01	0.46***	-				
8	[M] MSN1	-0.01	0.06	-0.02	-0.09**	-0.03	0.16***	0.16***	-			
9	[M] MSN2	-0.05	0.07*	0.03	0.02	0.01	0.22***	0.44***	0.04	-		
10	[M] PBC	0.03	0.10**	0.00	-0.06	0.01	0.28***	0.32***	0.19***	0.30***	-	
11	[D] MI	0.09*	-0.02	-0.01	0.02	-0.01	0.24***	0.23***	0.12***	0.06	0.12***	-
12	Mean	-	-	-	0.17	0.64	2.27	3.00	2.53	3.21	3.23	0.50
13	SD	-	-	-	0.19	0.37	0.75	0.69	0.61	0.65	0.58	0.37
14	CR	-	-	-	-	-	0.85	0.83	0.71	0.71	0.69	0.76

Note. [C]=control variable, [I]=independent variable, [M]=mediating variable, [D]=dependent variable

SES=socioeconomic status, MR1=the proportion of math teachers in the teaching staff, MR2= the proportion of math teachers that are qualified in the total teaching staff that is qualified, MPA1=math pursuit experiential attitudes, MPA2=math pursuit instrumental attitudes; MSN1=math subjective norms influenced by friends, MSN2=math subjective norms influenced by parents, PBC=perceived behavioral control, MI=math pursuit intention over other subjects

CR = Composite Reliability, SD = Standard deviation,

*** $p < .001$, ** $p < .01$, * $p < .05$

The items of the latent variable (6) ~ (10) were reverse-coded as having a four-point scale from strongly disagree (=1) to strongly agree (=4); The items for the latent variable were reverse-coded for a higher score to reflect high math intention (math intention = 1, otherwise = 0).

T-test

I ran a t-test to see whether there were statistical differences between an immigrant student group and a non-immigrant student group in the mean values of the six latent variables. The independent-samples t-test showed no significant difference between the mean values across the latent variables (Table 4.3). Though the immigrant student group had slightly higher mean values in five out of six latent variables regarding math motivation and intention, those differences are statistically insignificant.

Table 4.3

Descriptive Statistics and t test of Immigrant Status Group

	Variable name	Immigrant student group	Non-immigrant student group	
		Mean (SD)	Mean (SD)	*t* test
1	Math pursuit experiential attitudes	2.35 (0.73)	2.26 (0.75)	*t* = -1.28
2	Math pursuit instrumental attitudes	3.00 (0.63)	2.99 (0.70)	*t* = -0.09
3	Math subjective norms influenced by friends	2.49 (0.64)	2.54 (0.60)	*t* = 0.69
4	Math subjective norms influenced by parents	3.27 (0.66)	3.20 (0.65)	*t* = -1.09
5	Perceived behavioral control	3.25 (0.58)	3.23 (0.58)	*t* = -0.33
6	Math pursuit intention over other subjects	0.53 (0.37)	0.50 (0.37)	*t* = -0.82

Note. Mean (SD), ** p <=.01

Multilevel Measurement Model

As the data used in this study had a nested data structure (i.e., students were nested within school), I employed a multilevel CFA to test the latent structure of the scale items and investigate the validity. To demonstrate the appropriateness and usefulness of using a multilevel framework, this section presents the results of the intraclass correlation coefficients and Pearson correlation coefficients, followed by the results of the multilevel CFA.

Intraclass and Pearson Correlations

Table 4.4 demonstrates the Intraclass correlation coefficients (ICC) and the Pearson correlation coefficients assessed at both levels of the analysis. The ICC 1 values reflected the degree of the total variance associated with the school level. They indicate the extent to which students in the same school were similar in their math motivation (i.e., five latent variables, respectively) and math intention (one latent variable). The ICC 2 values denote the degree to which the groups' (i.e., school) means differ. The ICC 1 values ranged from less than 0.01 to 0.03, which demonstrates a very small amount of total variance occurring at the school level. The cut-off level of the ICC for assuming consistency of measures in the same unit is 0.10 (Lüdtke et al., 2011). The ICC 2 values ranged from -0.14 to 0.37, which was lower than the acceptable threshold of 0.7. The results of the two types of ICC values implied that the students in the same school in this study's dataset did not resemble each other in their math motivation and intention.

Table 4.4 shows that the three control variables (i.e., gender, SES, and race) had a statistically significant correlation with at least one of the dependent variables (e.g., gender and math pursuit instrumental variable α = - 0.36*). Therefore, it appeared reasonable that these three variables were set as a control variable in the hypothesized model at both levels. The latent and manifest correlations at level 2 revealed that both school's math resource variables (MR1 &

MR2) were not statistically correlated with aggregated students' math intention over other subjects, which indicated that the first hypothesis of the study might not be supported in a structural model. Next, aggregated student's math pursuit instrumental attitudes were positively correlated with aggregated student's math subjective norms influenced by parents (α = 0.62***), aggregated student's perceived behavioral control (α = 0.46**), and aggregated student' math pursuit intention over other subjects (α = 0.36*).

Table 4.4

Intraclass Correlation and Pearson Correlations for the Latent Variables at Both Levels

	Variable name	1	2	3	4	5	6	7	8	9	10	11
1	[C] Gender	-	0.04	-0.01	-	-	-0.02	-0.02	-0.01	-0.05	0.04	0.09**
2	[C] SES	0.15	-	-0.13***	-	-	0.03	0.04	0.06*	0.09**	0.12***	-0.03
3	[C] Race	0.06	-0.54***	-	-	-	-0.01	-0.02	0.01	0.00	-0.03	-0.02
4	[I] MR1	0.03	-0.22	0.21	-	-	-	-	-	-	-	-
5	[I] MR2	-0.16	0.15	0.00	-0.18	-	-	-	-	-	-	-
6	[M] MPA1	-0.02	-0.25	0.00	-0.03	0.07	-	0.48***	0.15***	0.22***	0.28***	0.24***
7	[M] MPA2	-0.36*	0.07	-0.15	0.02	0.04	0.19	-	0.16***	0.43***	0.31***	0.22***
8	[M] MSN1	-0.06	0.05	-0.31	-0.45	-0.15	0.28	0.16	-	0.04	0.19***	0.11**
9	[M] MSN2	-0.10	-0.21	0.30	0.09	0.04	0.32	0.62***	0.05	-	0.29***	0.05
10	[M] PBC	-0.16	-0.16	0.27	-0.23	0.05	0.29	0.46**	0.17	0.48**	-	0.13***
11	[D] MI	-0.12	0.04	0.09	0.12	-0.07	0.18	0.36*	0.17	0.23	0.16	-
12	Mean	-	-	-	0.17	0.64	2.27	3.00	2.53	3.21	3.23	0.50
13	SD	-	-	-	0.19	0.37	0.75	0.69	0.61	0.65	0.58	0.37
14	ICC1	-	-	-	-	-	0.02	0.01	0.01	0.00	0.03	0.00
15	ICC2	-	-	-	-	-	0.37	0.29	0.28	-0.14	0.48	0.12

Note. Correlations between level 1 variables are provided above the diagonal; Correlations between level 2 variables are presented below the diagonal

*p < 0.05, **p < 0.01, ***p < 0.001

[C]=control variable, [I]=independent variable, [M]=mediating variable, [D]=dependent variable SES=socioeconomic status, MR1=the proportion of math teachers in the teaching staff, MR2= the proportion of math teachers that are qualified in the total teaching staff that is qualified, MPA1=math pursuit experiential attitudes, MPA2=math pursuit instrumental attitudes; MSN1=math subjective norms influenced by friends, MSN2=math subjective norms influenced by parents, PBC=perceived behavioral control, MI=math pursuit intention over other subjects

Contrary to their relationships shown at level 2, at level 1, most of the latent variables were statistically significantly correlated. This result was in line with the results of the analysis of the inter correlation coefficients, which found that students within the same school did not share much resemblance.

Multilevel Confirmatory Factor Analysis

The multilevel CFA model was run to test the latent structure of the scaled items at level 1 and level 2. The six-factor model analysis yielded a set of acceptable fit values to the data except for the RMSEA value: χ^2 (df = *307)* = 828.81, p < .001), RMSEA = 0.04, SRMR= 0.68, CFI=0.93, TLI=0.92.

The factor loadings of most variables at level 1 were in the reasonable range: (a) math pursuit experiential attitudes: 0.61-0.75; (b) math pursuit instrumental attitudes: 0.57-0.70; (c) math subjective norms influenced by friends: 0.33-0.61; (d) math subjective norms influenced by parents: 0.47-0.69; (e) perceived behavior control: 0.46-0.47; (f) math intention over other subject 0.18-0.40. At level 2, all the factor loadings (ranging from 0.00-0.15) were less than the threshold of a good factor loading, 0.06. This result reaffirmed that schools might not play a substantial role in students' math motivation and intention.

Measurement Invariance Test

Measurement invariance was tested to ensure that comparisons across an immigrant student group and a non-immigrant student group were valid. As explained in this study's methodology section, the multiple group structural model had to be run at a single level as some level 1 variables had no variation within a cluster. For this reason, the measurement invariance test was run using a single-level CFA model (i.e., a six-factor model #4). I implemented the four consecutive steps in measurement tests: (1) configural invariance test, (2) metric invariance test (constrained loadings), (3) scalar invariance test (constrained loadings and intercepts), and (4) strict invariance test(constrained loadings, intercepts and residuals).

Table 4.5

The Results of the Four Measurement Invariance Tests

	1. Configural invariance	2. Weak/metric invariance	3. Strong/scalar invariance	4. Strict in invariance
$\chi^2(df)$	1075.24 (336)	1109.22 (356)	1139.01 (371)	1165.76 (392)
90% CI	[0.06, 0.07]	[0.06, 0.07]	[0.06, 0.07]	[0.06, 0.06]
RMSEA	0.06	0.06	0.06	0.06
SRMR	0.07	0.07	0.07	0.07
GFI	0.99	0.99	0.99	0.99
CFI	0.91	0.90	0.90	0.90
TLI	0.88	0.89	0.89	0.89

Note. 90% CI = 90% confidence interval, RMSEA: Root of Mean Square Error of Approximation, SRMR: Standardized Root Mean Square Residual, GFI: (Adjusted) Goodness of Fit, CFI: Comparative Fit Index, and TLI: Tucker-Lewis Index.

The results of the four measurement invariance tests showed evidence that there was no configural variance. The weak/metric model and strong/scalar model showed a statistical difference. The last model, "strict invariance," showed no statistical difference from the third strong/scalar invariance model. The analysis also showed that apart from the chi-square value with *df*, the other fit indices were the same across the four models (See Table 4.5).

First, the configural invariance model had a good fit. Second, the results of testing a weak/metric model in which the factor loadings were constrained to be equivalent across the groups showed that the RMSEA (=0.06), SRMR (=0.07), GFI (0.99), CFI (0.90), and TLI (0.89) values were the same as those of the first configural model. Additionally, the RMSEA value (0.06) fell within the others' confidence intervals, as recommended by Cheung and Rensvold (2002). However, the chi-square fit (χ^2) increased from 1075.24 to 1109.22, and the ANOVA test result indicated that the first and second models were a significantly different (p = 0.027*) from one another, which indicated non-invariance. While this result was surprising, the other indices besides the chi-square showed a good model fit, and the factor loadings were similar across the two groups. According to Cieciuch et al (2019, p. 16), as long as the theoretical model and measurement instrument are sound, non-invariance may be used as a useful source concerning group differences. Thus, I decided to move to the third model that tested the strong/scalar invariance.

Third, I tested the scalar invariance model by constraining factor loadings and intercepts to be equal across the groups. The results revealed that the scalar model had a good fit (χ^2(df = 371) = 1139.01 (p < .01), RMSEA = 0.06, 90% confidence interval [CI], [0.06, 0.07], SRMR = 0.07, GFI = 0.99, CFI = 0.90, TLI = 0.89). There was no change in the RMSEA, SRMR, GFI, CFI, and TLI values from those of the second model. Last, the strict invariance model constrained item residual variances to be equal across groups. The model indices and the ANOVA test results revealed that there was no statistically significant difference between the third and fourth models.

The set of the four measurement invariance tests demonstrated that the multigroup analysis could be valid. The model fit across the invariance was not ideal; however, the factor loadings were similar across the groups. Therefore, a multigroup path analysis was conducted to determine whether an immigrant student group and non-immigrant student group demonstrate statistically significant differences in the structural parameters. The following sections present the results of the structural model for the total sample, which is followed by the results of the multigroup path analysis across the groups.

Table 4.6

Descriptive Statistics of the Factor Loadings Across the Groups

	Latent Variable	Immigrant student group	Non-immigrant student group
		Mean (SD)	Mean (SD)
1	Math pursuit experiential attitudes	0.67 (0.10)	0.69 (0.06)
2	Math pursuit instrumental attitudes	0.55 (0.14)	0.64 (0.05)
3	Math subjective norms influenced by friends	0.55 (0.11)	0.51 (0.15)
4	Math subjective norms influenced by parents	0.61 (0.45)	0.55 (0.18)
5	Perceived behavioral control	0.47 (0.06)	0.48 (0.01)
6	Math pursuit intention over other subjects	0.32 (0.14)	0.33 (0.10)

Note. SD = Standard deviation

Structural Model

This section provides the results from the analysis of the path model. A 2-1-1 multilevel mediation SEM and a multiple group SEM were conducted to verify the path model and test three hypothesis:

(1) School's math resources (Schools that prioritizes resources for math over other subjects) are positively associated with students' intention (students' math intention over other subjects).

(2) The relationship between a school's mathematics resources and students' intention is mediated by students' motivation (i.e., math pursuit experiential and instrumental attitudes; subjective norms influenced by friends and parents, and perceived behavioral control).

(3) The effect of the school's mathematics resources on student intention will be stronger in the immigrant student group than in the non-immigrant student group.

The intent of first hypothesis was to measure the direct effect of the model. The intent of second hypothesis was to estimate the mediation effect, and that of the last hypothesis was to test the moderating effect. What follows are the analysis results that demonstrate the fit of the hypothesized model for the total sample and the two subsequent multigroup SEMs.

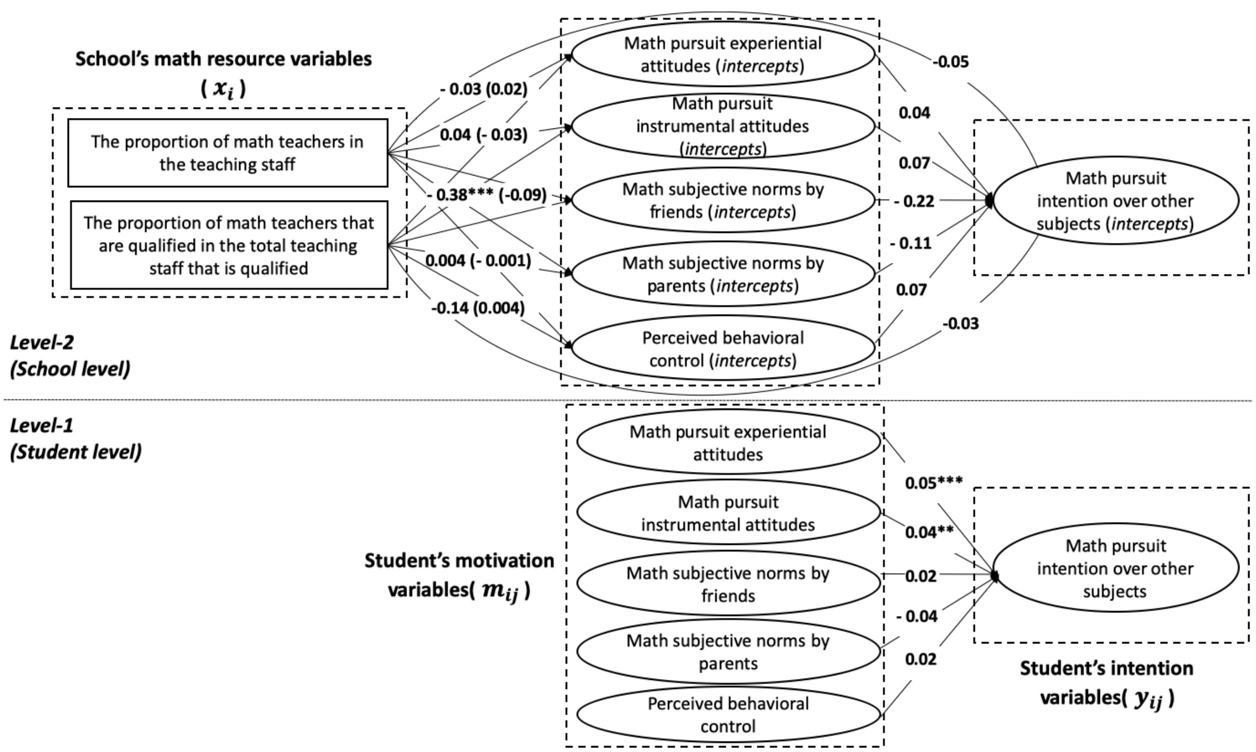
Structural Model Test for the Total Sample

The multilevel mediation SEM analysis involved examining direct and indirect paths from the school's math resources to students' math pursuit intention over other subjects mediated by student motivation variables. The structural model for the total sample was a 2-1-1 mediation SEM where the independent variables (i.e., school's math resources) were measured at level 2 (i.e., school level), and the other variables, mediators (i.e., student's motivation variable) and dependent variables (i.e., student's intention variable) were measured at level 1 (i.e., individual level). I specified random intercepts (i.e., cluster = school) and fixed slopes in the multilevel SEM. Technically, the mediation effects (i.e., indirect effects) were measured at level 2 by estimating the means of the student's motivation variables and student's intention variables at level 2. Figure 4.1 shows the results of the SEM model for the total sample. The goodness-of-fit indices for the first multilevel SEM for total sample showed an acceptable result: χ^2 (df = 485) = 1051.55 ($p < .001$), RMSEA = 0.03, SRMR = 0.34, CFI = 0.93, TLI = 0.91.

The first path model for the total sample revealed that school math resources (i.e., schools that prioritize resources for math over other subjects) are not statistically associated with students' intention to study math over other subjects in the long term. In other words, the first hypothesis was not supported in the model. Mediation analysis revealed that none of the student motivation variables statistically significantly mediated the relationship between school math resources and students' math intentions. Thus, the second research hypothesis was rejected.

Figure 4.1

Standardized Parameter Estimates for Pathways Among the Constructs for the Total Sample of the 2-1-1 Multilevel Mediation Model



Note: Each rectangle refers to an observed variable and each oval to a latent variable. For the sake of clarity, confounding variables are excluded from this figure. Among the standardized parameter estimates presented between the school's math resource variables and the student's motivation variables, the values on the left are standardized parameter estimates for pathways from “the proportion of math teachers in the teacher staff” to a corresponding student’s motivation variable. The other values in parentheses are the estimates for pathways from “the proportion of math teachers that are qualified in the total teaching staff that is qualified” to a corresponding student’s motivation variable.

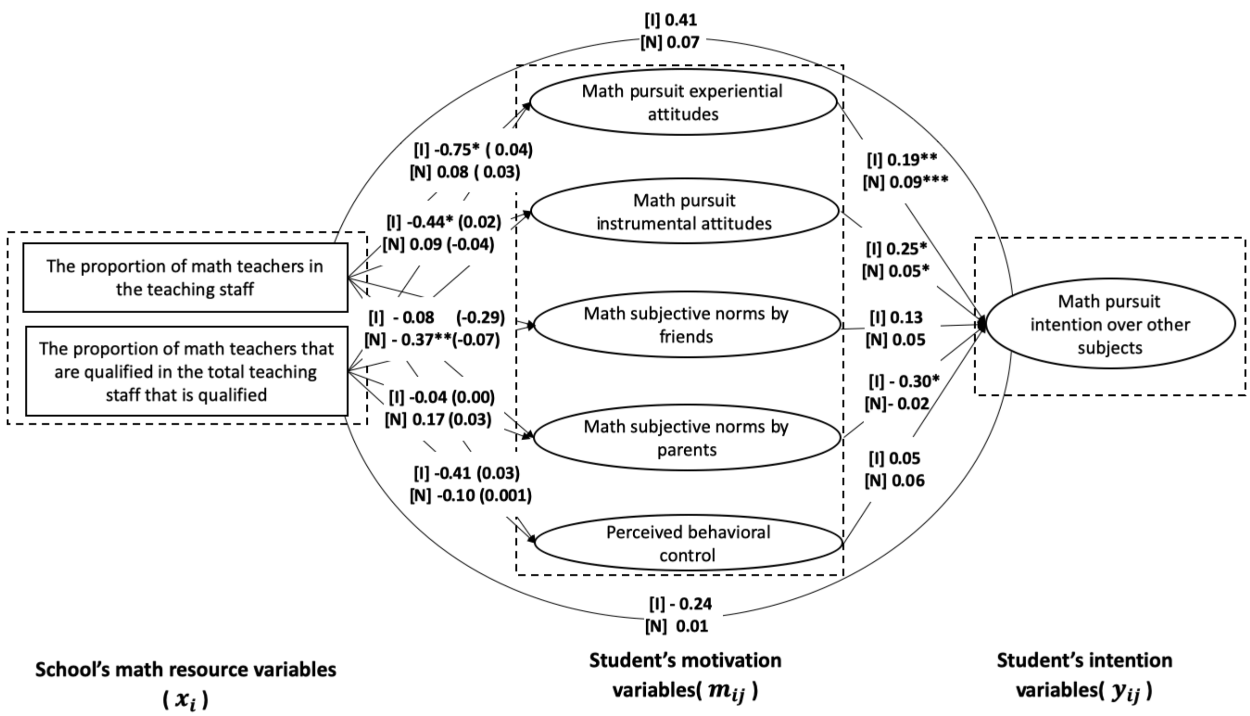
Though the first two hypotheses were rejected, there were some interesting findings from this model. A student’s math pursuit intention over other subjects were statistically and positively associated with his/her math pursuit experiential attitudes (β = 0.05, SD: 0.02 , $p < 0.001$) and math pursuit instrumental attitudes (β = 0.04, SD: 0.02 , $p < 0.001$). These associations were statistically significant at the student’s level (Level 1) but not at the school level (Level 2). These results indicated that a student’s math pursuit intention over other subjects was likely to depend on individual factors and not much on the effect of school resources allocation.

Multigroup path analysis

To test the third hypothesis of this study, that the effect of the school’s mathematics resources on student intention will be stronger in the immigrant student group than in the non-immigrant student group, I estimated the multigroup SEM model that compared the regression parameters of the two groups. The goodness-of-fit indices for this model indicated the conflicting results as to whether the hypothesized model had an acceptable fit: χ^2 (df = 488) = 1952.86 ($p < .001$), RMSEA = 0.07, SRMR = 0.12, GFI = 0.99, CFI = 0.81, TLI = 0.78. The RMSEA and GFI values indicated the hypothesized model had a good fit, but the other fit indices demonstrated that it did not fit the data well. Figure 4.2 presented earlier in this chapter provides the results of the standardized parameter estimates for pathways among the variables for the multigroup model. First, none of these groups showed a direct or indirect effect of school math resources on students' intention to study math over other subjects in the long term. Therefore, this study's last hypothesis was not supported.

Figure 4.2

Standardized Parameter Estimates for Pathways Among the Constructs of the Multiple Group Model Comparing an Immigrant Student Group with a Non-immigrant Student Group



Note: [I] = immigrant student group, [N] = non-immigrant student group.

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

Each rectangle refers to an observed variable and each oval to a latent variable. For the sake of clarity, confounding variables are excluded from this figure. Among the standardized parameter estimates presented between the school's math resource variables and the student's motivation variables, the values on the left without parentheses are standardized parameter estimates for pathways from "the proportion of math teachers in the teacher staff" to a corresponding student's motivation variable. The other values in parentheses are the estimates for pathways from "the proportion of math teachers that are qualified in the total teaching staff that is qualified" to a corresponding student's motivation variable.

However, there were other interesting findings. One of the two school math resource variables, the proportion of math teachers in the teaching staff, showed some statistical significance with other variables, whereas the other school math resources did not (See Figure 4.2). Additionally, as the theory of planned behavior suggests, this study's data showed that some student's math motivation variables statistically significantly predicted students' math pursuit intention over other subjects: (1) students' math pursuit experiential attitudes and students' intention variables: [Immigrant group] $\beta = 0.19$ ($p < 0.01$) & [Non-immigrant group] $\beta = 0.09$ ($p < 0.01$); (2) students' math pursuit instrumental attitudes and students' intention variables [Immigrant group] $\beta = 0.25$ ($p < 0.01$) & [Non-immigrant group] $\beta = 0.05$ ($p < 0.01$). However, students' math subjective norms influenced by parents were negatively associated with students' intention variables only for the immigrant student group.

The two groups showed differences in the size, direction, and significance of some regression coefficients. To emphasize the differences across these two groups, I created Table 4.7, which includes only the standardized regression parameters with statistically significant differences. Reading this table alongside Figure 4.2 may enhance the comparison. There were four cases in which only one of the groups showed a statistical significance in their regression coefficients: (1) a school's proportion of math teachers in the teaching staff was negatively associated with an immigrant student group's math pursuit experiential attitudes ($\beta = -0.75$, SD: 0.35 , $p < 0.05$), but not with those of a non-immigrant student group ($\beta = 0.08$, SD: 0.11 , $p > 0.05$); (2) a school's proportion of math teachers' in the teaching staff was negatively linked to an immigrant student group's math pursuit instrumental attitudes ($\beta = -0.44$, SD: 0.21 , $p <$

0.05), but not with those of a non-immigrant student group (β = 0.09, SD: 0.11 , $p > 0.05$); (3) a school's proportion of math teachers' in the teaching staff was negatively associated with an non-immigrant student group's math subjective norms influenced by friends (β = -0.37, SD: 0.11 , $p < 0.01$), but not with those of an immigrant student group (β = -0.08, SD: 0.25 , $p > 0.05$); (4) students' math subjective norms influenced by parents were statistically and negatively linked to an immigrant student group's math pursuit intention over other subjects (β = -0.30, SD: 0.15 , $p < 0.01$), but not with that of a non-immigrant student group's one (β = -0.10, SD: 0.03 , $p > 0.05$).

Table 4.7

The Standardized Regression Coefficients Showing a Statistical Significance in the Multiple Group Path Model

Group	Dependent	Independent	Coeff-icient	z value	p-value (Sig)
I	Math pursuit intention over other subjects	Math pursuit experiential attitudes	0.19	2.78	0.005**
	Math pursuit intention over other subjects	Math pursuit instrumental attitudes	0.25	2.05	0.040*
	Math pursuit intention over other subjects	Math subjective norms influenced by parents	-0.30	-2.04	0.041*
	Math pursuit experiential attitudes	The proportion of math teachers in the teaching staff	-0.75	-2.12	0.034*
	Math pursuit instrumental attitudes	The proportion of math teachers in the teaching staff	-0.44	-2.08	0.037*
N	Math pursuit intention over other subjects	Math pursuit experiential attitudes	0.09	3.76	<0.001***
	Math pursuit intention over other subjects	Math pursuit instrumental attitudes	0.05	2.15	0.031*
	Math subjective norms influenced by friends	The proportion of math teachers in the teaching staff	-0.37	-3.41	0.001***

Note. I = immigrant student group, N = non-immigrant student group.

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

I also ran comparisons between the multiple group model with free parameters and the multiple group model in which equality constraints were imposed on regression parameters. The ANOVA test found that the difference in chi-square between these two models was statistically different: (χ^2 (*df* = 12) = 390.47, $p < 0.001$). This result indicated that the paths of the constructs differed between the immigrant student group and non-immigrant student group. Therefore, I can conclude these two groups showed different statistical associations in the following linkages. (a) The proportion of math teachers in the teaching staff – math pursuit experiential attitudes; (b) The proportion of math teachers in the teaching staff – math pursuit instrumental attitudes; (c) The proportion of math teachers in the teaching staff – math subjective norms influenced by friends; (d) Math pursuit experiential attitudes – math pursuit intention over other subjects; (e) Math pursuit instrumental attitudes – math pursuit intention over other subjects; (f) Math subjective norms influenced by parents – math pursuit intention over other subjects.

Chapter Summary

The results of the multilevel SEM model for the total sample presented that, at the school level (level 2), the school's math resources had no statistically significant direct and indirect effects on aggregated students' intentions to pursue math over other subjects. However, at the student level (level 1), students' experiential and instrumental attitudes toward the pursuit of math were positively related to students' intentions to pursue math over other subjects. The results of the multiple group path analysis comparing immigrant and non-immigrant student groups also found that the school's math resources had no statistically significant direct and indirect effects on students' intentions to pursue math over other subjects. However, a statistical difference in the overall path model of these two groups was found. Students in the immigrant group were less likely than non-immigrant students to be motivated to study math when the school had a larger proportion of math teachers in the teaching staff. Additionally, the immigrant students' intentions to study math over other subjects were positively associated with their math pursuit experiential and instrumental attitudes but negatively linked to their math subjective norms as influenced by their parents.

CHAPTER FIVE

SUMMARY, DISCUSSIONS AND IMPLICATIONS

The previous chapter presented the results of this dissertation study. This chapter first section provides the summary of the study, including the purpose, research questions, and methodology. The next section is a discussion of the results of the study. The conclusions and implications section also provides the limitations of the study and some recommendations for further research.

Summary

Drawing on the theory of planned behavior framework, in this study, the aimed was to conceptually model and statistically evaluate how a school environment that prioritizes math over other subjects might influence students' intentions to pursue math over other academic subjects in the long term. This study examined the following three research questions.

1. How does a school that prioritizes resources for school math over other subjects (regressors *x*) influence students' exhibiting intentions to pursue math over other subjects (outcome *y*)?
2. Is the resulting effect mediated by students' math pursuit attitudes, subjective norms, perceived behavioral control (mediators *m*)
3. Does this effect change with students' immigrant standing (moderator *z*)?"

This study is conceptually unique in that it captured students' math motivation in relation to other subjects, rather than independently from other subjects. Using the 2012 U.S. PISA dataset, which was the year in which, the PISA survey collected data on variables that are part of the theory of planned behavior. The data of a total of 1,108 students nested in 36 schools were analyzed. This analysis was methodologically rigorous. I used multiple imputations by chained equation (i.e., predictive mean matching) to minimize biased estimates that could be generated from the PISA 2012's rotated sampling design. The study employed a multilevel SEM framework to estimate the measurement and structural model for the total sample. However, for the multiple group analysis (an immigrant student group & a non-immigrant student group), a single level measurement and structural model were conducted due to the small cluster size of the data. The SEM model analysis for the total sample yielded results showing that there was no direct effect of a school's math resources on the students' intentions to pursue math over other subjects (Hypothesis 1). Also, no mediation effect of student's math motivation was found in this relationship (Hypothesis 2). The multiple group SEM model analysis found that the immigrant student group and non-immigrant student group had a statistically significant difference in their path models. However, school math resources were not found to have either direct and indirect effect on these two groups' intention to study math in the long term and pursue math-intensive careers.

In the following discussion section, I situate the analytical methods and research findings (Hypotheses 1, 2, & 3) in relation to previous studies.

Discussion of the Results of the Study

There has been a growing consensus among researchers that incorporating social, psychological, and educational factors would extend the structural model of the theory of planned behavior and increase the theory's explanatory power (Areepattamannil et al., 2016). To this literature, the current study added consideration of school math resources as an independent variable to test a plausible alternative model. The results demonstrated that school math resources were not statistically associated with students' intentions to pursue math over other subjects. This result may indicate that solely attending a math-oriented school does not guarantee that students will be motivated to prefer math over other subjects in the long term. Specifically, in this study, school math resources were measured as the proportion of math teachers within the teaching staff and the proportion of math teachers who hold a bachelor's degree and who hold a bachelor degree's in math. This result means that teachers' advanced degrees cannot statistically predict student's math intentions. This result is consistent with some earlier studies (Croninger et al., 2007; Palardy & Rumberger, 2008; Williams & Williams, 2011), but is in contrast to Rice's (2003) finding that the more teachers have advanced degrees, the more likely their students have high achievement.

This study suggests that when teachers' effect on students' math motivation is measured at an adequate level (i.e., school-level), the relationship might not be as robust as the No Child Left Behind (NCLB) advocates believed it to be.

Again, the direct effect of the quantity and quality of math teachers on students' preference for math over other subjects in the long term was found to be statistically insignificant. These results may suggest the need to examine alternative measures of math teachers' quality. Numerous studies have addressed such measures of teachers' quality as their attitudes (Lazarides et al., 2018), their support of students (Yu & Singh, 2018), and their participation in professional development (Stipek et al., 1998). Math teacher's certifications and advanced degrees have benefits from a policy point of view. They are relatively easily translated into criteria for evaluating teachers' expertise compared to observing their actual classroom practices. However, the current study's results may imply that NCLB and the educational trends that they generated might benefit from exploring more appropriate criteria for selecting math teachers likely to improve students' math motivation. The estimated insignificant direct effect of the school's math resources on the student's intention to prioritize math over other subject also requires exploring mediators that might demonstrate the indirect effects.

The results of the test of the second hypothesis found no mediation effects of the components of the theory of planned behavior in the overall SEM for the total sample as well as the SEM for the immigrant group. This result is different from most previous studies, which found that students' attitudes, subjective norms, and perceived control behaviors could predict their intentions (Foltz et al., 2015; Moore & Burrus, 2019; Porche et al., 2016). This difference may stem from the current study's integration of the school-level variable and a multilevel framework. The current study's finding was that the school math resources did not increase aggregated school-level students' preference for math over other subjects via aggregated school-level students' math motivation. Future studies using the multilevel framework and integrating school-level variables could extend the field's understanding of the mediating roles of students' attitudes, subjective norms, and perceived control behavior.

At Level 1 (i.e., student level), some motivation variables were statistically associated with the intention variable, but the relationship was not statistically significant at Level 2. The relationship between residual ratings of math motivation dimension and residual ratings of math intention dimension was measured at Level 1. Students' math pursuit experiential attitudes and math pursuit instrumental attitudes were positively linked to their intention to pursue math over other subjects. These results at Level 1 are in accordance with Lipnevich et al., (2011), who found that among the three student math motivation variables (i.e., math pursuit attitudes, math subjective norms, and perceived behavior control), students' math attitudes most statistically significantly predict their math intention. However, the current study's finding of an statistically insignificant relationship between students' math subjective norms and math intentions was in contrast with Foltz et al.'s (2015) finding. This discrepancy may be attributed to the different age groups in the two studies (i.e., undergraduate vs. middle schoolers) and their different definitions of subjective norms.

In regards to the mediators, it is noteworthy that in this study a six-factor model was used that separated math pursuit attitudes into (a) math pursuit experiential attitudes and (b) math pursuit instrumental attitudes, and math subjective norms into (c) math subjective norms influenced by friends and (d) math subjective norms influenced by parents, whereas math pursuit attitudes and math subjective norms were not subdivided in previous empirical studies, in which a four-factor model was used. However, for this study, the data analysis showed that subdividing these two factors provided more nuanced results. For example, the two constructs, (a) math subjective norms influenced by friends and (b) math subjective norms influenced by parents, showed a substantial mean difference ($M= 2.53$ & $M=3.21$, respectively), Their correlation coefficients were also found to be statistically insignificant. Thus, the current study suggests that researchers might employ the six-factor model of the theory of planned behavior rather than the four-factor model.

The third hypothesis of the current study posited that the association between the school's math resources and students' intentions to pursue math over other subjects would be stronger for immigrant than for non-immigrant student groups. However, analysis using the multiple group SEM model did not support this hypothesis. There was no statistically significant difference between the two groups in terms of the direct relationship between school math resources and their math intentions. This result was congruent with the multilevel SEM model for the total sample that showed no direct effect between school math resources and students' intentions.

Although no difference between the two groups in the magnitude of the direct effect was observed, the result of the multiple group path analysis was statistically different. This difference between the two groups in the path model is plausible in that various studies have found that culturally different groups presented divergent patterns in the relationships of the construct of the theory of planned behavior (Arditzoglou & Crawley III, 1992; F. A. Lee, 2012; Lipnevich et al., 2011, 2016).

In the present study, the multiple group path analysis showed a statistically negative association between the school's proportion of math teachers in the teaching staff and the immigrant student group's experiential and instrumental math pursuit attitudes as well as their math subjective norms influenced by friends. That is, the greater the proportion of math teachers on the staff, the less likely that immigrant students were motivated to study math, while there was no statistically significant association for the non-immigrant student group. This seemingly paradoxical negative association for the immigrant group challenges the conventional wisdom that immigrant students attending a math-intensive school would be more motivated to pursue further math studies and calls for in-depth inquiry into the math motivation of immigrant students through interviews.

On the other hand, with regards to the relationship between students' motivation variables and intention variables, immigrant students showed a stronger positive effect than non-immigrant students of math pursuit experiential attitudes and math pursuit instrumental attitudes on their intentions to pursue math over other subjects. In particular, the strong association between the immigrant group's math intentions and math pursuit instrumental attitudes (a measure of students' perception of the importance of math for their future) is aligned with Cho and Hwang's longitudinal ethnographic study (2019). Thus, it seems plausible that immigrant students view math as having instrumental value by preparing them to pursue math-intensive careers that can lead to their success in society.

Additionally, unlike the non-immigrant student group, the immigrant student group presented a statistically negative relationship between their perceived parents' emphasis on the importance of studying math and their pursuit of learning math in the long term. This result contradicts the findings of previous research showing that positive family involvement substantially encouraged immigrant students to pursue the math field (Chachashvili-Bolotin et al., 2019; Onuma et al., 2020). This incongruence may reflect limitations in the data used in this study, which did not capture complexities within the immigrant student group, such as students' national origins (Dronkers & Levels, 2007; Levels et al., 2008).

Conclusions and Implications of the Study

Many educational researchers who accept the validity of the theory of planned behavior have empirically tested the relationships among its constructs. However, studies that consider the nested data structure and school-level variables remain rare in the literature. The integration of school-level variables means that planned behavior is no longer considered as solely an intra-personal variable but as responsive to contextual influences (Burić & Kim, 2020). This approach is beneficial as it can help find a practical way to increase students' math motivation.

Findings from this research contribute to the scarce empirical evidence regarding the effects of school-level variables, particularly the quantity and quality of math teachers within a school, on students' long term math intentions. In this study, no direct or mediation effect of school math resources was found when these were indicated by (a) the proportion of the math teachers in the teaching staff and (b) the proportion of math teachers that are qualified in the entire staff that is qualified. This finding can be used as a policy implication that teacher selection based on a teacher's bachelor's degree attainment and/or bachelor's degree with a math-related major may not meaningfully improve students' math motivation and intention, in contrary to the assumption of the NCLB legislation. Basing judgment of teachers' quality solely on their undergraduate major and achievement of teacher certification may falsely predict a positive impact on students' math motivation. Policymakers may want to focus primarily on an alternative measure of teacher quality that can be observed in classroom practice such as how mathematics teachers communicate with other students. One of the reasons that the U.S. states utilized a mathematic teacher's bachelor's degree attainment and certification attainment as criteria of the teacher quality comes from its relative simplicity than measuring teacher attitudes, practice, and beliefs (Huang & Moon, 2009). The results of this study encourage to consider other valuable measures of teacher quality despite its possible more effort to evaluate that effectiveness on students' motivations.

This study also provides a novel conceptual framework that captures students' relative levels of math motivation in comparison with motivation in other subjects. The consideration of relative preference in this study is more plausible considering that students have preferences among subjects. This empirically and practically sensitive framework is vital in understanding students' math motivation. This approach also extends the theory of planned behavior by examining the applicability and predictive power of the theory when students' intentions to pursue math *over* another subject is added. Also, given the fitness of most schools' resource availability, in this study the effect of the level of school resources dedicated to math relative to other subjects was examined. This approach warrants further research to fine-tune the theory of planned behavior to reflect reality better.

This study was methodologically rigorous in that it employed a multiple imputation method (i.e., predictive mean matching) and multilevel structural equation modeling in analyzing the 2012 U.S. PISA dataset to test the hypotheses. The predictive mean matching method enabled replacement of missing values with values that were statistically similar to the original dataset. The multilevel structural equation modeling found that aggregated students' math motivation and intention at the school level has no statistically significant link, in contradiction to previous findings in which the relationship was measured at a student level. The results obtained here emphasize the use of a multilevel framework for a hierarchical data structure in which students are nested within school to measure the examined constructs accurately and minimize measurement error.

Given the results from this research that showed the statistical difference in math motivation and math intention between an immigrant student group and a non-immigrant student group, educators may develop intervention strategies. They might investigate what types of motivation variables to modify to increase students' intentions to study math. For example, the results of this study imply that immigrant students are less likely to take math courses and pursue math careers if their parents overly emphasize the necessity of studying math. Educators may open a discussion platform in which parents and students freely talk about their perceptions of learning math.

The demand for math-intensive careers in the U.S. has continually increased, and schools play a critical role in engaging students in studying math. Schools and educational policies need to develop practices that enhance students' math motivation while considering students' interests and a school's available resources. Although this study is limited to a sample of the U.S. eighth and ninth graders, its results shed light on how students are motivated to pursue math in the long term and suggest that successful intervention strategies can differ according to students' immigration standing.

Limitations and Recommendations for Future Research

A few limitations of this study should be noted in relation to future research. First, this study was based on the U.S. 2012 PISA dataset and employed a cross-sectional design, which does not support conclusions regarding causal links between the target constructs. The typically strong assumptions required for drawing causal inferences can rarely be met in international large scale assessment data (Rutkowski & Delandshere, 2016). This study’s findings have to be interpreted cautiously, keeping in mind that the statistical associations found between the variables do not prove causation. Recently, a growing body of research has addressed the issue of drawing causal inferences with large-scale assessment data from a Bayesian perspective (Kaplan, 2016; Kaplan & McCarty, 2013). Future studies may address the possible causal ordering of the constructs of the theory of planned behavior measured in the PISA dataset.

Another limitation of the current study was the possible sampling bias of the PISA dataset due to its rotated sampling design. To overcome this challenge, I applied a multiple imputations by chained equation approach, specifically a predictive mean matching method, which Kaplan and Su (2016) proved to be a valid approach in dealing with the 2012 PISA dataset. Indeed, the imputed values had a distribution similar to that of the original dataset. Also, to reduce the possible sampling bias of a math-intensive school being selected by students already interested in math, my sample included only students who were attending a math-intensive school by default, having no other option. Nevertheless, there was no guarantee of zero sampling bias. Future studies may wish to minimize the sampling bias using other advanced imputation techniques.

Third, the integration of the multilevel framework in the examination of intraclass correlation coefficients indicated that students within the same school did not share a similar degree of math motivation and math intention. The failure to meet the threshold value of ICC 1 (> 0.1) and ICC2 (> 0.7) suggested by Lüdtke et al. (2011) should be noted in interpreting the results. This study's approach is still valuabINle in that a multilevel framework was employed in measuring the relationships among the constructs of the planned of behavior. I suggest future research to examine the relationships among the constructs at both the between-level (i.e., student level) and the within-level (i.e., school level) for accurate measurement of the effect. One option that could be examined among school resources can be curriculum and educational materials, as this study only human resources in math instruction were considered.

Fourth, the measurement models had a reasonable but not perfect fit to the data. Some variables showed low factor loadings (e.g., ST48Q01), and low discriminant validity was observed as some latent variables had statistically significant correlation coefficients. However, the current study represented a novel step in the use of a six-factor model for analysis, which improved content validity and discriminant validity both theoretically and empirically. This six-factor model showed a better model fit (χ^2(*df*=485) = 1051.55, p < 0.001) than a four-factor model (χ^2(*df* =174) = 876.46, *p* < 0.001). Also, the six-factor model exhibited higher reliability coefficients. Future researchers may continue to test this six-factor model of the theory of planned behavior. Accumulation of the empirical findings may further validate the six-factor model's superiority over four-factor models and help re-specify the constructs of the theory of planned behavior.

Fifth, the third hypothesis was tested at the student level of analysis even though students were nested within the school level. This single-level multiple group path analysis was unavoidable given the warning of *R* software against the situation in which "one or more individual-level variables have no variation within a cluster." The inability to implement multilevel multiple group analysis can be partially attributed to the small sample size and cluster size of the immigrant student group. Despite this apparent limitation of the analysis, I made sure to carry out the necessary procedure to run a multiple group path analysis. I ran a four-step model invariance test to establish model invariance across the groups. Researchers interested in measuring the school math resource effect on these two groups' math motivation in a multilevel framework may wish to collect data with a larger sample size and cluster size than that of the 2012 U.S. PISA dataset.

Sixth, this study did not reflect complexities within an immigrant student group in measuring their math motivation and intention. In this study, student variables that had statistically significant correlations with latent factors (gender, socioeconomic status, and race/ethnicity) were controlled. However, numerous differences within an immigrant student group, such as an immigration generation, which could influence their math motivation, were omitted due to a restricted immigrant student sample size (Chachashvili-Bolotin et al., 2019; Chu, 2009; Onuma et al., 2020; Porche et al., 2016; Takeuchi, 2018). Immigrant students' country of origin and country of destination were not considered in this study as the data from U.S 2012 PISA questionnaire did not reveal them in public. Future researchers may wish to develop a survey designed to capture the complex nature of an immigrant student group and administer it to a sufficiently large immigrant student sample.

Last, next year, 2022, OECD's PISA will administer their triannual questionnaire and the focus will be devoted to mathematics. I have a plan to replicate the analysis of the current study to the data from 2022 questionnaire to evaluate the sensitivity of this study's results to cohort and time variation. The results of the sensitivity test will allow to test the generalizability of the current study's results.

REFERENCES

Adler, J. (2000). Conceptualising Resources as a Theme for Teacher Education. *Journal of Mathematics Teacher Education*, *3*(3), 205–224. https://doi.org/10.1023/A:1009903206236

Adnot, M., Dee, T., Katz, V., & Wyckoff, J. (2017). Teacher Turnover, Teacher Quality, and Student Achievement in DCPS. *Educational Evaluation and Policy Analysis*, *39*(1), 54–76. https://doi.org/10.3102/0162373716663646

Ajzen, I. (1991). The Theory of Planned Behavior Organizational Behavior and Human Decision Processes. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Ajzen, I., & Driver, B. (1992). Application of the theory of planned behavior to leisure choice. *Journal of Leisure Research*, *24*(3), 207–224.

Ajzen, I., & Icek Ajzen. (2006). Constructing a theory of planned behavior questionnaire. *Available at People. Umass. Edu/Aizen/Pdf/Tpb. Measurement. Pdf*, 1–7. Retrieved from http://people.umass.edu/~aizen/pdf/tpb.measurement.pdf

American Immigration Council. (2017). Foreign-born STEM Workers in the United States, 1–20. Retrieved from https://www.americanimmigrationcouncil.org/sites/default/files/research/foreign-born_stem_workers_in_the_united_states_final.pdf

Amrai, K., Motlagh, S. E., Zalani, H. A., & Parhon, H. (2011). The relationship between academic motivation and academic achievement students. *Procedia - Social and Behavioral Sciences*, *15*, 399–402. https://doi.org/10.1016/j.sbspro.2011.03.111

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Aragon, S. (2016). Teacher shortages: What we know. *Education Commission of the States*, (May), 1–12. Retrieved from https://eric.ed.gov/?id=ED565893

Arditzoglou, S. Y., & Crawley III, F. E. (1992). Structural Equation Modeling of Science and Mathematics Achievements of Secondary I Females in Arab Jerusalem: An Application of the Theory of Planned Behavior. *Paper Presented at the Annual Meeting of the National Association for Research in Science Teaching(Boston, MA, March, 1992)*, (1). Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED348230&site=ehost-live

Areepattamannil, S. (2012). and Science Self-Concepts and Their Achievement, 695–716.

Areepattamannil, S., Abdelfattah, F., Mahasneh, R. A., Khine, M. S., Welch, A. G., Melkonian, M., & Al Nuaimi, S. A. (2016). International note: Prediction of mathematics work ethic and performance from behavioral, normative, and control beliefs among Qatari adolescents. *Journal of Adolescence*, *46*, 38–44. https://doi.org/10.1016/j.adolescence.2015.10.016

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94.

Baldwin, S. A., & Fellingham, G. W. (2013). Bayesian methods for the analysis of small sample multilevel data with a complex variance structure. *Psychological Methods*, *18*(2), 151–164. https://doi.org/10.1037/a0030642

Ballou, D. (1996). Do public schools hire the best applicants? *Quarterly Journal of Economics*, *111*(1), 97–133. https://doi.org/10.2307/2946659

Barwell, R., Moschkovich, J. N., & Setati-Phakeng, M. (2017). *Language diversity and mathematics: Second language, bilingual, and multilingual learners*. *Compendium for research in mathematics education*. Reston, VA: National Council of Teachers of Mathematics.

Bentler, P. M. (1990). Quantitative methods in psychology: Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238–246.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588–606. https://doi.org/10.1037/0033-2909.88.3.588

Bhochhibhoya, A., & Branscum, P. (2018). The Application of the Theory of Planned Behavior and the Integrative Behavioral Model towards Predicting and Understanding Alcohol-Related Behaviors: A Systematic Review. *Journal of Alcohol & Drug Education*, *62*, 39–63.

Blanchard, C. M., Rhodes, R. E., Nehl, E., Fisher, J., Sparling, P., & Courneya, K. S. (2003). Ethnicity and the Theory of Planned Behavior in the Exercise Domain. *American Journal of Health Behavior*, *27*(6), 579–591. https://doi.org/10.5993/AJHB.27.6.1

Bollen, K. A. (1989). *Structural equations with latent variables. Structural equations with latent variables.* Oxford, England: John Wiley & Sons. https://doi.org/10.1002/9781118619179

Breda, T., & Napp, C. (2019). Girls ' Comparative Advantage in Reading Can Largely Account for the Gender Gap in Math-Intensive Fields Girls ' Comparative Advantage in Reading Can Largely Account for the Gender Gap in Math-Intensive Fields. *Proceedings of the*

National Academy of Sciences, *116*(31), 15435–15440.

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), 230–258.

Burrus, J., & Moore, R. (2016). The incremental validity of beliefs and attitudes for predicting mathematics achievement. *Learning and Individual Differences*, *50*, 246–251. https://doi.org/10.1016/j.lindif.2016.08.019

Caplan, N., Choy, M. H., & Whitmore, J. K. (1991). Children of the boat people: A study of educational success. In *University of Michigan Press*. University of Michigan Press.

Chachashvili-Bolotin, S., Lissitsa, S., & Milner-Bolotin, M. (2019). STEM outcomes of second-generation immigrant students with high-skilled parental backgrounds. *International Journal of Science Education*, *41*(17), 2465–2483. https://doi.org/10.1080/09500693.2019.1686549

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Chiu, M. M., & Khoo, L. (2005). Effects of resources, inequality, and privilege bias on achievement: Country, school, and student level analyses. *American Educational Research Journal*, *42*(4), 575–603. https://doi.org/10.3102/00028312042004575

Cho, E., & Hwang, S. (2019). Exploring changes in multi-ethnic students' mathematics achievement motivation. *Journal of the Korean Society of Mathematical Education Series A: The Mathematical Education*, *58*(1), 101–120.

Chu, S.-Y. (2009). Implementation of Supportive School Programs for Immigrant Students in the

United States. *Preventing School Failure: Alternative Education for Children and Youth*, *53*(2), 67–72. https://doi.org/10.3200/psfl.53.2.67-72

Cieciuch, J., Davidov, E., Schmidt, P., & Algesheimer, R. (2019). How to Obtain Comparable Measures for Cross-National Comparisons. *Kolner Zeitschrift Fur Soziologie Und Sozialpsychologie*, *71*, 157–186. https://doi.org/10.1007/s11577-019-00598-7

Close, K., Amrein-Beardsley, A., & Collins, C. (2018). State-level assessments and teacher evaluation systems after the passage of the every student succeeds act: Some steps in the right direction. *National Education Policy Center*, *0249*(June). Retrieved from http://nepc.colorado.edu/publication/state-assessment

Cohen, D. K., & Hill, H. C. (2000). Instructional policy and classroom performance: The mathematics reform in California. *Teachers College Record*, *102*(2), 294–343. https://doi.org/10.1111/0161-4681.00057

Coleman, J. S., States, U., & Statistics, N. C. for E. (2004). Equality of educational opportunity [summary report]. In *Washington: U.S. Dept.*

Committee on STEM Education. (2018). Charting a Course for Success: America's Strategy for STEM Education. *National Science and Technology Council*, (December), 1–35. Retrieved from http://www.whitehouse.gov/ostp.

Cowan, J., Goldhaber, D., Hayes, K., & Theobald, R. (2016). Missing Elements in the Discussion of Teacher Shortages. *Educational Researcher*, *45*(8), 460–462. https://doi.org/10.3102/0013189X16679145

Croninger, R. G., Rice, J. K., Rathbun, A., & Nishio, M. (2007). Teacher qualifications and early learning: Effects of certification, degree, and experience on first-grade student achievement.

Economics of Education Review, *26*(3), 312–324. https://doi.org/10.1016/j.econedurev.2005.05.008

Darling-Hammond, L. (2000). Teacher quality and student achievement: A review of state policy evidence. *Education Policy Analysis Archives*, *8*(1), 1–44. https://doi.org/10.14507/epaa.v8n1.2000

de Araujo, Z., Roberts, S. A., Willey, C., & Zahner, W. (2018). English Learners in K–12 Mathematics Education: A Review of the Literature. *Review of Educational Research*, *88*(6), 879–919. https://doi.org/10.3102/0034654318798093

Depaoli, S., & Clifton, J. P. (2015). A Bayesian Approach to Multilevel Structural Equation Modeling With Continuous and Dichotomous Outcomes. *Structural Equation Modeling*, *22*(3), 327–351. https://doi.org/10.1080/10705511.2014.937849

Di Martino, P., & Zan, R. (2001). Attitude toward mathematics: some theoretical issues. *Conference: 25th Conference of the International Group for the Psychology of Mathematics Education*, *3*(July), 209–216. Retrieved from https://www.researchgate.net/publication/265049550_Attitude_toward_mathematics_some_theoretical_issues

Dorn, E., Hancock, B., Sarakatsannis, J., & Viruleg, E. (2020). COVID-19 and student learning in the United States: The hurt could last a lifetime. *McKinsey & Company*, (June), 1–14. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Industries/Public and Social Sector/Our Insights/COVID-19 and student learning in the United States The hurt could last a lifetime/COVID-19-and-student-learning-in-the-United-States-FINAL.pdf%0Ahttps://www.mckinse

Doyle, C. (1890). *The sign of four*. London, England: Spencer Blackett.

Dronkers, J., & Levels, M. (2007). Do school segregation and school resources explain region-of-origin differences in the mathematics achievement of immigrant students? *Educational Research and Evaluation*, *13*(5), 435–462. https://doi.org/10.1080/13803610701743047

Ehrenberg, R. G., & Brewer, D. J. (1994). Do school and teacher characteristics matter? Evidence from High School and Beyond. *Economics of Education Review*, *13*(1), 1–17. https://doi.org/10.1016/0272-7757(94)90019-1

Ehrenberg, R. G., & Brewer, D. J. (1995). Did teachers' verbal ability and race matter in the 1960s? Coleman revisited. *Economics of Education Review*, *14*(1), 1–21. https://doi.org/10.1016/0272-7757(94)00031-Z

Enders, C. K. (2010). *Applied missing data analysis*. Guilford press.

Fang, J., Wen, Z., & Hau, K. T. (2019). Mediation Effects In 2-1-1 Multilevel Model: Evaluation Of Alternative Estimation Methods. *Structural Equation Modeling*, *26*(4), 591–606. https://doi.org/10.1080/10705511.2018.1547967

Fayer, S., Lacey, A., & Watson, A. (2017). STEM occupations: Past, present, and future. *Spotlight on Statistics*, (January), 1–35.

Ferguson, R. F. (1991). Paying for Public Education: New Evidence on How and Why Money Matters. *Harvard Journal on Legislation*, *28*, 465–497.

Fetter, M. (2001). Mass Imputation of Agricultural Economic Data Missing by Design A Simulation Study of Two Regression Based Techniques. *Federal Conference on Survey Methodology*.

Fishbein, M., Von Haeften, I., & Appleyard, J. (2001). The role of theory in developing effective interventions: Implications from project SAFER. *Psychology, Health and Medicine*, *6*(2), 223–238. https://doi.org/10.1080/13548500123176

Fishbein, Martin, & Ajzen, I. (2011). *Predicting and changing behavior: The reasoned action approach*. *Taylor & Francis* (Taylor & F). https://doi.org/10.4324/9780203838020

Floyd, R. G., Evans, J. J., & McGrew, K. S. (2003). Relations between measures of cattell-horn-carroll (CHC) cognitive abilities and mathematics achievement across the school-age years. *Psychology in the Schools*, *40*(2), 155–171. https://doi.org/10.1002/pits.10083

Foltz, L. G., Foltz, C. B., & Kirschmann, S. L. (2015). Planning for science, technology, engineering, and math (STEM) retention: Understanding the implications of the theory of planned behavior. *Planning for Hgher Education Journal*, *43(4)*(September), 17–26.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Fuligni, A. J. (1997). The Academic Achievement of Adolescents from Immigrant families: The roles of family background, attitudes, and behavior. *Child Development*, *68*(2), 351–363. https://doi.org/10.1086/447358

Gibson, M. A., & Ogbu, J. U. (1991). Minority status and schooling: A comparative study of immigrant and involuntary minorities. In *Garland Publishing*. New York, NY: Garland Publishing.

Godin, G., & Kok, G. (1996). The theory of planned behavior: a review of its applications to health-related behaviors. *American Journal of Health Promotion*, *11*(2), 87–98.

Goldhaber, D. D., & Brewer, D. J. (2000). Does teacher certification matter? High school teacher certification status and student achievement. *Educational Evaluation and Policy Analysis*, *22*(2), 129–145. https://doi.org/10.3102/01623737022002129

Gutiérrez, R. (2013). The sociopolitical turn in mathematics education. *Journal for Research in Mathematics Education*, *44*(1), 37–68. https://doi.org/10.5951/jresematheduc.44.1.0037

Hagger, M. S., & Hamilton, K. (2020). Effects of socio-structural variables in the theory of planned behavior: a mediation model in multiple samples and behaviors. *Psychology and Health*, *0*(0), 1–27. https://doi.org/10.1080/08870446.2020.1784420

Hair, J. F. J., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis (7th ed.)*. Upper Saddle River, NJ: Prentice.

Hallinan, M. T. (1994). School Differences in Tracking Effects on Achievement. *Social Forces*, *72*(3), 799–820. https://doi.org/10.1093/sf/72.3.799

Hamilton, K., & White, K. M. (2012). Social Influences and the Physical Activity Intentions of Parents of Young-Children Families: An Extended Theory of Planned Behavior Approach. *Journal of Family Issues*, *33*(10), 1351–1372. https://doi.org/10.1177/0192513X12437151

Hillmert, S. (2013). Links between immigration and social inequality in education: A comparison among five European countries. *Research in Social Stratification and Mobility*, *32*(1), 7–23. https://doi.org/10.1016/j.rssm.2013.02.002

Hom, P. W., Tsui, A. S., Wu, J. B., Lee, T. W., Zhang, A. Y., Fu, P. P., & Li, L. (2009). Explaining Employment Relationships With Social Exchange and Job Embeddedness. *Journal of Applied Psychology*, *94*(2), 277–297. https://doi.org/10.1037/a0013453

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55.

https://doi.org/10.1080/10705519909540118

Huang, F. L., & Moon, T. R. (2009). Is experience the best teacher? A multilevel analysis of teacher characteristics and student achievement in low performing schools. *Educational Assessment, Evaluation and Accountability*, *21*(3), 209–234. https://doi.org/10.1007/s11092-009-9074-2

Ingersoll, R. M., & Perda, D. (2009). The mathematics and science teacher shortage : Fact and myth. *CPRE (Consortium for Policy Research) Research Report (3-2009)*, 45.

James, L. R., Brett, J. M., Demaree, R. G., Dugas, J. L., Gustafson, S. B., & Jones, A. P. (1984). Mediators, Moderators, and Tests for Mediation Mulaik, and Gernt Wolf for their helpful suggestions and advice Requests for reprints should be sent to. *Journal of Applied Psychology*, *69*(2), 307–321.

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, *34*(2), 183–202.

Jöreskog, K. G., & Sörbom, D. (1986). LISREL VI: Analysis of linear structural relationships by maximum likelihood, instrumental variables, and least squares methods. Scientific Software.

Kalinec-Craig, C. A. (2014). Examining My Window and Mirror : A Pedagogical Reflection from a White Mathematics Teacher Educator about Her Experiences with Immigrant Latina Pre-service Teachers. *Association of Mexican-American Educators*, *8*(2), 45–54.

Kaplan, D. (2016). Causal inference with large-scale assessments in education from a Bayesian perspective: a review and synthesis. *Large-Scale Assessments in Education*, *4*(1). https://doi.org/10.1186/s40536-016-0022-6

Kaplan, D., & McCarty, A. T. (2013). Data fusion with international large scale assessments: a case study using the OECD PISA and TALIS surveys. *Large-Scale Assessments in Education*, *1*(1), 1–53. https://doi.org/10.1186/2196-0739-1-6

Kaplan, D., & Su, D. (2016). On Matrix Sampling and Imputation of Context Questionnaires With Implications for the Generation of Plausible Values in Large-Scale Assessments. *Journal of Educational and Behavioral Statistics*, *41*(1), 57–80. https://doi.org/10.3102/1076998615622221

Kaylene, & Caroline C. Williams. (2011). Five key ingredients for improving student motivation. *Res High Educ J*, *12*, 1–23. Retrieved from https://scholarsarchive.library.albany.edu/cgi/viewcontent.cgi?article=1000&context=math_fac_scholar

Khisty, L. L., & Chval, K. B. (2002). Pedagogic discourse and equity in mathematics: When teachers' talk matters. *Mathematics Education Research Journal*, *14*(3), 154–168. https://doi.org/10.1007/BF03217360

Koenka, A. C. (2020). Academic motivation theories revisited: An interactive dialog between motivation scholars on recent contributions, underexplored issues, and future directions. *Contemporary Educational Psychology*, *61*, 101831. https://doi.org/10.1016/j.cedpsych.2019.101831

Kruschke, J. K., & Vanpaemel, W. (2015). Bayesian estimation in hierarchical models. *The Oxford Handbook of Computational and Mathematical Psychology*, 279–299.

Kwahk, K. (2019). Structural equation modeling using R: Analysis procedure and method. *Knowledge Management Research*, *20*(1), 1–26.

Larrabee, H. A., & Tyack, D. B. (1976). The One Best System: A History of American Urban Education. *The New England Quarterly*, *49*(1), 155. https://doi.org/10.2307/364577

Lazarides, R., Buchholz, J., & Rubach, C. (2018). Teacher enthusiasm and self-efficacy, student-perceived mastery goal orientation, and student motivation in mathematics classrooms. *Teaching and Teacher Education*, *69*, 1–10. https://doi.org/10.1016/j.tate.2017.08.017

Lee, F. A. (2012). Applying the theory of planned behavior to educational goals and intentions: Understanding the challenges and views of low income african american adolescents using a mixed method approach. *Doctoral Dissertation, Wichita State University*, (December).

Lee, S. Y. (1981). A bayesian approach to confirmatory factor analysis. *Psychometrika*, *46*(2), 153–160. https://doi.org/10.1007/BF02293896

Levels, M., Kraaykamp, G., & Dronkers, J. (2008). Immigrant children's educational achievement in western countries: Origin, destination, and community effects on mathematical performance. *American Sociological Review*, *73*(5), 835–853. https://doi.org/10.1177/000312240807300507

Lipnevich, A. A., MacCann, C., Krumm, S., Burrus, J., & Roberts, R. D. (2011). Mathematics Attitudes and Mathematics Outcomes of U.S. and Belarusian Middle School Students. *Journal of Educational Psychology*, *103*(1), 105–118. https://doi.org/10.1037/a0021949

Lipnevich, A. A., Preckel, F., & Krumm, S. (2016). Mathematics attitudes and their unique contribution to achievement: Going over and above cognitive ability and personality. *Learning and Individual Differences*, *47*, 70–79. https://doi.org/10.1016/j.lindif.2015.12.027

Little, R. J., & Rubin, D. B. (2019). Statistical analysis with missing data (Vol. 793). John Wiley

& Sons.

Liu, E., Rosenstein, J. G., Swan, A. E., & Khalil, D. (2008). When Districts Encounter Teacher Shortages: The Challenges of Recruiting and Retaining Mathematics Teachers in Urban Districts. *Leadership and Policy in Schools*, *7*(3), 296–323. https://doi.org/10.1080/15700760701822140

Lou, C. (2020). Evidence Reveals Children of Immigrants' Shared Diversity and Ties to America _ Urban Institute. Retrieved from https://www.urban.org/urban-wire/evidence-reveals-children-immigrants-shared-diversity-and-ties-america

Lüdtke, O., Marsh, H. W., Robitzsch, A., & Trautwein, U. (2011). A 2x2 taxonomy of multilevel latent contextual models: Accuracy-bias trade-offs in full and partial error-correction models. *Psychological Methods*, *16*(4), 444–467.

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure analysis: the problem of capitalization on chance. *Psychological Bulletin*, *111*(3), 490–504.

Mannion, E. (2016). Autonomy, Race, and State Reproduction of Status: Durkheim and Weber on Education and Immigration. *Critical Sociology*, *42*(4–5), 699–714. https://doi.org/10.1177/0896920514544042

Marsh, H., & Hau, K.-H. (2003). Relations between academic self-concept and achievement in mathematics and language: Cross-cultural generalisability. *Paper Presented at the Joint AARE/NZARE Conference Aukland*. Retrieved from https://www.aare.edu.au/data/publications/2003/hau03756.pdf

Marsh, H. W. (1986). Verbal and math self-concepts: An internal/external frame of reference model. *American Educational Research Journal*, *23*(1), 129–149.

Marsh, Herbert W, & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First- and higher order factor models and their invariance across groups. *Psychological Bulletin*, *97*(3), 562–582. https://doi.org/10.1037/0033-2909.97.3.562

Maxwell, L. A. (2014). U. S. school enrollment hits majority-minority milestone. *The Education Digest*, *80*(4), 1–7. Retrieved from https://www.edweek.org/ew/articles/2014/08/20/01demographics.h34.html

Miura, I. T., Okamoto, Y., Kim, C. C., Steere, M., & Fayol, M. (1993). First Graders' Cognitive Representation of Number and Understanding of Place Value: Cross-National Comparisons-France, Japan, Korea, Sweden, and the United States. *Journal of Educational Psychology*, *85*(1), 24–30. https://doi.org/10.1037/0022-0663.85.1.24

Miura, I. T., Okamoto, Y., Vlahovic-Stetic, V., Kim, C. C., & Han, J. H. (1999). Language Supports for Children's Understanding of Numerical Fractions: Cross-National Comparisons. *Journal of Experimental Child Psychology*, *74*(4), 356–365. https://doi.org/10.1006/jecp.1999.2519

Montaño, D. E., & Kasprzyk, D. (2015). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. *Health Behavior: Theory, Research and Practice*, 95–124.

Moore, R., & Burrus, J. (2019). Predicting STEM Major and Career Intentions With the Theory of Planned Behavior. *Career Development Quarterly*, *67*(2), 139–155. https://doi.org/10.1002/cdq.12177

Moschkovich, J. (2002). A Situated and Sociocultural Perspective on Bilingual Mathematics

Learners. *Mathematical Thinking and Learning*, *4*(2–3), 189–212. https://doi.org/10.1207/s15327833mtl04023_5

Moschkovich, J. (2007). Using two languages when learning mathematics. *Educational Studies in Mathematics*, *64*(2), 121–144. https://doi.org/10.1007/s10649-005-9005-1

Moschkovich, J. (2013). Principles and guidelines for equitable mathematics teaching practices and materials for English language learners. *Journal of Urban Mathematics Education*, *6*(1), 45–57. Retrieved from http://ed-osprey.gsu.edu/ojs/index.php/JUME/article/viewArticle/204

Murnane, R. J., & Phillips, B. R. (1981). Learning by doing, vintage, and selection: Three pieces of the puzzle relating teaching experience and teaching performance. *Economics of Education Review*, *1*(4), 453–465. https://doi.org/10.1016/0272-7757(81)90015-7

Niepel, C., Burrus, J., Greiff, S., Lipnevich, A. A., Brenneman, M. W., & Roberts, R. D. (2018). Students' beliefs and attitudes toward mathematics across time: A longitudinal examination of the theory of planned behavior. *Learning and Individual Differences*, *63*(June 2017), 24–33. https://doi.org/10.1016/j.lindif.2018.02.010

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory (3rd ed.)*. NY: McGraw-Hill, Inc.

OECD. (2012). *PISA 2012 Assessment and Analytical Framework. Mathematics, Reading, Science, Problem Solving and Financial Literacy*. *Echinoderms: Durham - Proceedings of the 12th International Echinoderm Conference*. Paris: OECD Publishing. https://doi.org/10.1201/9780203869543-c92

Olivos, E. M., & Mendoza, M. (2010). Immigration and educational inequality: Examining

Latino immigrant parents’ engagement in U.S. public schools. *Journal of Immigrant and Refugee Studies*, *8*(3), 339–357. https://doi.org/10.1080/15562948.2010.501301

Onuma, F. J., Berhane, B., & Fries-Britt, S. L. V. (2020). “I’ve Always Been in Private School”: The Role of Familial Norms and Supports in Black Immigrant Students’ Preparation for STEM Majors. *Journal of Diversity in Higher Education*. https://doi.org/10.1037/dhe0000285

Palardy, G. J., & Rumberger, R. W. (2008). Teacher effectiveness in first grade: The importance of background qualifications, attitudes, and instructional practices for student learning. *Educational Evaluation and Policy Analysis*, *30*(2), 111–140. https://doi.org/10.3102/0162373708317680

Pimm, D. (2019). *Speaking mathematically (1987): Communication in mathematics clasrooms*. *Routledge* (Vol.4). Routledge. https://doi.org/10.4324/9781315278858

Planas, N., & Civil, M. (2009). Working with mathematics teachers and immigrant students: An empowerment perspective. *Journal of Mathematics Teacher Education*, *12*(6), 391–409. https://doi.org/10.1007/s10857-009-9116-1

Porche, M. V., Grossman, J. M., & Dupaya, K. C. (2016). New American scientists: First generation immigration status and college STEM aspirations. *Journal of Women and Minorities in Science and Engineering*, *22*(1), 1–21. https://doi.org/10.1615/JWomenMinorScienEng.2016015227

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, *42*(1), 185–227. https://doi.org/10.1080/00273170701341316

Preacher, K. J., Zhang, Z., & Zyphu, M. J. (2011). Alternative methods for assessing mediation in multilevel data: The advantages of multilevel sem. *Structural Equation Modeling*, *18*(2), 161–182. https://doi.org/10.1080/10705511.2011.557329

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods*, *15*(3), 209–233. https://doi.org/10.1037/a0020141

Rahman, T., Fox, M. A., Ikoma, S., & Gray, L. (2017). Certification Status and Experience of U.S. Public School Teachers: Variations across Student Subgroups. NCES 2017-056. *National Center for Education Statistics*. Retrieved from https://files.eric.ed.gov/fulltext/ED573196.pdf

Rässler, S. (2002). *Statistical matching: A frequentist theory, practical applications, and alternative Bayesian approaches (Vol. 168)*. Springer Science & Business Media.

Raudenbush, S. W., & Bryk, A. S. (1992). *Hierarchical Linear Models: Applications and Data Analysis Methods*. *Sage Publications*. https://doi.org/10.1016/B0-12-369398-5/00166-3

Razfar, A. (2012). ¡Vamos a Jugar Counters! Learning Mathematics Through Funds of Knowledge, Play, and the Third Space. *Bilingual Research Journal*, *35*(1), 53–75. https://doi.org/10.1080/15235882.2012.668868

Razfar, A. (2013). Multilingual Mathematics: Learning Through Contested Spaces of Meaning Making. *International Multilingual Research Journal*, *7*(3), 175–196. https://doi.org/10.1080/19313152.2012.665204

Rice, J. K. (2003). *Teacher quality: Understanding the effectiveness of teacher attributes*. *Economic Policy Institute*. Washington, DC.

Rivkin, S., Hanushek, E., & Kain, J. (2005). Teachers, schools, and academic achievement. *Econometrica*, *73*(2), 417–458.

Rubin, D. B. (1987). Multiple imputations in sample surveys. *Proceedings of the Survey Research Methods Section, American Statistics Association*, 20–28.

Rubin, D. B. (2004). *Multiple imputation for nonresponse in surveys (Vol. 81)*. John Wiley & Sons.

Rubin, Donald B. (1976). Inference and Missing Data. *Biometrika*, *63*(3), 581–592.

Rusá, Š., Komárek, A., Lesaffre, E., & Bruyneel, L. (2018). Multilevel moderated mediation model with ordinal outcome. *Statistics in Medicine*, *37*(10), 1650–1670. https://doi.org/10.1002/sim.7605

Rutkowski, D., & Delandshere, G. (2016). Causal inferences with large scale assessment data: using a validity framework. *Large-Scale Assessments in Education*, *4*(1), 1–18. https://doi.org/10.1186/s40536-016-0019-1

Santos, S. L., Suarez-Orozco, C., & Suarez-Orozco, M. (1995). *Transformations: Migration, Family Life, and Achievement Motivation among Latino Adolescents. Stanford University Press*. Stanford University Press. https://doi.org/10.2307/2547238

SAS. (2017). *SAS/STAT 14.3 User ' s Guide Introduction to Survival Analysis Procedures*.

Schleicher, A. (2006). Where immigrant students succeed: a comparative review of performance and engagement in PISA 2003: © OECD 2006. *Intercultural Education*, *17*(5), 507–516. https://doi.org/10.1787/9789264023611-7-en

Schleppegrell, M. J. (2007). The linguistic challenges of mathematics teaching and learning: A research review. *Reading and Writing Quarterly*, *23*(2), 139–159.

https://doi.org/10.1080/10573560601158461

Schüz, B. (2017). Socio-economic status and theories of health behaviour: Time to upgrade a control variable. *British Journal of Health Psychology*, *22*(1), 1–7. https://doi.org/10.1111/bjhp.12205

Schwartz, A. E., & Stiefel, L. (2004). Immigrants and the distribution of resources within an urban school district. *Educational Evaluation and Policy Analysis*, *26*(4), 303–327. https://doi.org/10.3102/01623737026004303

Sikora, J., & Pokropek, A. (2021). Immigrant optimism or immigrant pragmatism? Linguistic capital, orientation towards science and occupational expectations of adolescent immigrants. *Large-scale Assessments in Education, 9*(1), 1-24.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research. *Journal of Consumer Research*, *15*(3), 325. https://doi.org/10.1086/209170

Smith-davis, J. (2002). Immigrant Students with Disabilities in the U . S . Public Schools : Preliminary Findings of a Pilot Study.

Smith, T. M., Desimone, L. M., & Ueno, K. (2005). "Highly qualified" to do what? the relationship between NCLB teacher quality mandates and the use of reform-oriented instruction in middle school mathematics. *Educational Evaluation and Policy Analysis*, *27*(1), 75–109. https://doi.org/10.3102/01623737027001075

Snijders, T. A. B., & Bosker, R. (1999). Multilevel anlaysis: An introduction to basic and advanced multilevel modeling. In *Sage*. London, UK: Sage.

Stanton-Salazarm, R., & Dornbusch, S. (1995). Social Capital and the Reproduction of

Inequality : Information Networks among Mexican-Origin High School Students Author (s): Ricardo D . Stanton-Salazar and Sanford M . Dornbusch Source : Sociology of Education , Apr ., 1995 , Vol . 68 , No . 2 (Apr. *Sociology of Education*, *68*(2), 116–135.

Steele, D. F. (2001). Using Sociocultural Theory to Teach Mathematics: A Vygotskian Perspective. *School Science and Mathematics*, *101*(8), 404–416. https://doi.org/10.1111/j.1949-8594.2001.tb17876.x

Steinberg, L., Dombusch, S. M., & Brown, B. B. (1992). Ethnic differences in adolescent achievement an ecological perspective. *Cognitive and Moral Development, Academic Achievement in Adolescence*, *47*(6), 723–729. https://doi.org/10.1037//0003-066x.47.6.723

Stipek, D., Givvin, K. B., Salmon, J. M., & Macgyvers, V. L. (1998). Can a teacher intervention improve classroom practices and student motivation in mathematics? *Journal of Experimental Education*, *66*(4), 319–337. https://doi.org/10.1080/00220979809601404

Suhr, D. (2003). *The basics of structural equation modelig*. *University of Northern Colorado. https://www.lexjansen.com/wuss/2006/tutorials/TUT-Suhr.pdf [accessed 2 May 2021]*. https://doi.org/10.1007/s007840050036

Takeuchi, M. A. (2018). Power and identity in immigrant parents' involvement in early years mathematics learning. *Educational Studies in Mathematics*, *97*(1), 39–53. https://doi.org/10.1007/s10649-017-9781-4

Turner, E. E., & Celedón-Pattichis, S. (2011). Mathematical Problem Solving Among Latina/o Kindergartners: An Analysis of Opportunities to Learn. *Journal of Latinos and Education*, *10*(2), 146–169. https://doi.org/10.1080/15348431.2011.556524

van de Schoot, R., Lugtig, P., & Hox, J. (2012). A checklist for testing measurement invariance.

European Journal of Developmental Psychology, *9*(4), 486–492. https://doi.org/10.1080/17405629.2012.686740

van de Schoot, R., Winter, S. D., Ryan, O., Zondervan-Zwijnenburg, M., & Depaoli, S. (2017). A systematic review of Bayesian articles in psychology: The last 25 years. *Psychological Methods*, *22*(2), 217–239. https://doi.org/10.1037/met0000100

Van Lancker, W., & Parolin, Z. (2020). COVID-19, school closures, and child poverty: a social crisis in the making. *The Lancet Public Health*, *5*(5), e243–e244. https://doi.org/10.1016/S2468-2667(20)30084-0

Vink, G., Frank, L. E., Pannekoek, J., & van Buuren, S. (2014). Predictive mean matching imputation of semicontinuous variables. *Statistica Neerlandica*, *68*(1), 61–90. https://doi.org/10.1111/stan.12023

von Davier, M. (2013). Imputing Prociency Data under Planned Missingness in Population Models. *Handbook of International Large-Scale Assessment: Background, Technical Issues, and Methods of Data Analysis*, 175–201. https://doi.org/10.1201/b16061-13

Wang, L. P., & Preacher, K. J. (2015). Moderated Mediation Analysis Using Bayesian Methods. *Structural Equation Modeling*, *22*(2), 249–263. https://doi.org/10.1080/10705511.2014.935256

Waters, M. C. (1994). Ethnic and racial identities of second-generation black immigrants in New York City. *International Migration Review*, *28*(4), 795–820. https://doi.org/10.2307/2547158

Weaver, W. T. (1983). America's teacher quality problem: alternatives for reform. In *New York: Praeger*. New York: Praeger.

Wenglinsky, H. (2002). How schools matter: The link between teacher classroom practices and students academic performance. *Education Policy Analysis Archives*, *10*(12), 1–30.

Wheaton, B., Muthén, B. O., Alwin, D. F., & Summers, G. F. (1977). Assessing Reliability and Stability in Panel Models Author (s): Blair Wheaton , Bengt Muthén , Duane F . Alwin and Gene F . Summers Published by : Wiley Stable URL : http://www.jstor.org/stable/270754 ASSESSING RELIABILITY AND STABILITY. *Sociological Methodology*, *8*(1), 84–136.

Wiley, D. E., & Yoon, B. (1995). Teacher Reports on Opportunity to Learn : Analyses of the 1993 California Learning Assessment System (CLAS). *Educational Evaluation and Policy Analysis*, *17*(3), 355–370.

Wulff, J. N., & Ejlskov, L. (2017). Multiple imputation by chained equations in praxis: Guidelines and review. *Electronic Journal of Business Research Methods*, *15*(1), 41–56.

Xu, K. (2012). Multiple group measurement invariance analysis in Lavaan. *Cambridge Mass*, 37. Retrieved from http://users.ugent.be/~yrosseel/lavaan/multiplegroup6Dec2012.pdf%5Cnpapers3://publication/uuid/E3BA0810-80DA-4C3E-9FCD-76DA7C27C400

Yu, R., & Singh, K. (2018). Teacher support, instructional practices, student motivation, and mathematics achievement in high school. *Journal of Educational Research*, *111*(1), 81–94. https://doi.org/10.1080/00220671.2016.1204260

Zhang, Z., Zyphur, M. J., & Preacher, K. J. (2009). Testing multilevel mediation using hierarchical linear models: Problems and solutions. *Organizational Research Methods*, *12*(4), 695–719. https://doi.org/10.5465/ambpp.2008.33716518

Zou, X., & Savani, K. (2019). Descriptive norms for me, injunctive norms for you: Using norms to explain the risk gap. *Judgment and Decision Making*, *14*(6), 644–648.

Zyphur, M. J., Zhang, Z., Preacher, K. J., & Bird, L. J. (2019). Moderated mediation in multilevel structural equation models: Decomposing effects of race on math achievement within versus between high schools in the United States. *The Handbook of Multilevel Theory, Measurement, and Analysis.*, 473–494. https://doi.org/10.1037/0000115-021