SIMILARITIES AND DIFFERENCES IN MATH-RELATED MOTIVATION AND INTENTION TO PURSUE MATH IN THE FUTURE: A CROSS-NATIONAL STUDY IN THE UNITED STATES AND SOUTH KOREA

Hyeyoung Hwang

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Approved by:

Judith L. Meece

William B. Ware

Jeffrey A. Greene

Xue Lan Rong

Sooyong Byun

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ABSTRACT

Hyeyoung Hwang: Similarities and Differences in Math-Related Motivation and Intention to Pursue Math in the Future: A Cross-National Study in the United States and South Korea
(Under the direction of Judith Meece)

Research on adolescents' academic motivation has examined predictors of academic behavior for several decades. Guided by expectancy-value theories of academic motivation (Eccles et al., 1983; Wigfield & Eccles, 2000), this study examined the relations between motivational beliefs and intentions to pursue math in the future, with a particular focus on the mediating role of current math performance. The study also explored cross-national cultural similarities and differences in these relations, using samples of 15-year-old U.S. and South Korean adolescents. The target sample included a total of three thousand (*N*= 3,341) 15-year-old adolescents (1,689 South Korean sample and 1,652 U.S. sample), who participated in the Programme for International Student Assessment (PISA) of 2012. Results provided evidence that expectancy beliefs (i.e., math self-concept) and value beliefs (i.e., math interest and math utility value) were directly associated with future intentions to pursue mathematics for South Korean and U.S. student samples. The mediating role of current math performance in explaining these relations was only documented for the U.S. sample but not South Korean sample. Math self-concept was associated with math performance for both samples; however, there was a positive association between math utility and math performance for only South Korean sample. Consistent with prior research, there was a positive relation between math performance and math intentions, as well as a negative relation between math anxiety and math performance. These

predicted relations were found for the U.S. sample of adolescents, but similar relations were not evident for the South Korean sample. This study adds to motivation research by addressing the unique influence of various motivation constructs in explaining adolescents' academic choices and by providing insights into the accumulation of knowledge in the expectancy-value model of achievement motivation for a cross-national perspective.

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LIST OF ABBREVIATIONS AND SYMBOLS

CFA	Confirmatory Factor Analysis
CI	Confidence interval
d	Cohen's measure of sample effect size for comparing two sample means
df	Degrees of freedom
FIML	Full information maximum likelihood
ISCED	International Standard Classification of Education
Korea	South Korea
MACS	Mean and covariance structure
MCAR	Missing completely at random
N/n	Number of cases
ns	Not statistically significant
p	P-value
PISA	Programme for International Student Assessment
R^2	Variance explained
SD	Standard deviation
SE	Standard error
SEM	Structural equation modeling
WLSMV	Weighted least squares multivariate estimation
±	Plus or minus
λ	Lamda, factor loading
$\Delta\chi^2$	DIFFTEST Chi-square difference test
χ^2	DIFFTEST Chi-square

CHAPTER 1: INTRODUCTION

A series of large-scale international studies using the Trends in International Mathematics and Science Study (TIMSS) and the Programme for International Student Assessment (PISA) document significant achievement across countries. When compared with students in East Asia, American students consistently underperform in math and science (e.g., Lee, 2000; Marsh & Hau, 2004). For example, the PISA 2009 results show that the United States (U.S.) ranked 25th in math and 17th in science out of the 34 member nations of the Organization for Economic Cooperation and Development (OECD). By contrast, most East Asian countries including Shanghai, Singapore, Taiwan, South Korea, and Japan continue to outpace the U.S. Arne Duncan, former U.S.Secretary of Education, has called the scores of underperforming U.S. students a "brutal truth" that "must serve as a wake-up call against educational complacency and low expectations" (as cited in Schaffhauser, 2013). Test scores offer evidence in support of arguments that the U.S. is losing ground to global competitors in an increasingly technological society (Duhigg & Bradshaw, 2012) and that a decade's worth of school reform has done little to improve educational outcomes (Gabriel & Dillon, 2011).

Why has adolescents' math and science test score been an important subject of concern and discussion of each nation? One of the main reasons is that satisfactory achievement and preparation, especially in mathematics, has been identified as a critical filter for educational and career choices (Finn, Gerber, & Wang, 2002). Math serves as a foundation for in-demand

STEM[1]-related careers, and, it is even associated with development in social sciences, communication and political sciences (Kadijevich, 1998). Even though the number of STEM-related jobs is expected to surge in the years to come, about 60% of U.S. students, including even those who begin high school interested in science or math, decide not to pursue STEM majors or careers upon graduation (Morella & Kurtzleban, 2013). The nation is already suffering a major shortage of domestic skilled employees as more than half a million manufacturing jobs are going unfilled and largely resorting to overseas resources (Morella & Kurtzleban, 2013). Thus, the recruitment and retention of adolescents in future STEM fields is one of most prevailing issues facing the education systems nationwide (e.g., Fox, 2008; OECD, 2010).

The high school years are recognized as a particularly important period for adolescents to make choices about whether or not to stay in the math and science-related fields in the future (Tan, Barton, Kang & O'Neill, 2013). It is very difficult to embark upon a STEM trajectory after beginning college due to the required curricula in STEM fields (Tyson, 2011). Inadequate math achievement during high school sometimes acts as a structural filter in that it prevents adolescents from pursuing a STEM trajectory because students have not gained the mathematical knowledge to enter STEM-related career fields at the required point. Adolescents' course enrollment patterns in high school often limit their access to STEM fields. A recent study (Sadler & Tai, 2007) indicates that college students who completed advanced math courses during high school perform significantly better in a range of STEM-related college courses. More importantly, for the current discussion, adolescents' desire or intention to pursue math in their future affects their actual decisions to stay in math and science education tracks. Specifically, Tai and colleagues (2006) found that 14-year-old students with expectations of science-related

[1] STEM refers to the physical, biological, medical, health and computer sciences; technology; engineering; and mathematics

careers were 3.4 times more likely to earn STEM-related degrees than students without similar expectations.

In the U.S., many young high school students are underprepared for math and, regrettably, even those with the potential for math achievement believe that mathematics is not relevant to their future career goals and thus show low intention to pursue math in the future (Parsad & Lewis, 2003). As a result, encouraging students and promoting strong intentions to pursue math have become part of an enduring mission for educators, researchers, and policymakers. A number of studies from psychological, sociological, and educational perspectives have attempted to find possible contributing factors that facilitate or inhibit intentions of pursuing math-related endeavors.

Does Motivation Matter in Understanding Intentions to Pursue Math in the Future?

Academic choice behavior results from a complicated array of interrelated variables: students' ability in math, attitudes and perceptions, parent and peer influence, socioeconomic status, quality of mathematic instruction in school, and so forth. While home- and family-related variables are mostly outside of the control of educators, attitudinal and affective variables, including *achievement motivation*, are relatively amenable to change by educational interventions and, in recent decades, have emerged as notable predictors of academic behavior (Linnenbrink & Pintrich, 2002). Achievement motivation involves internal processes by which goal-directed behaviors are initiated and sustained in academic situations (Schunk, Meece, & Pintrich, 2014). Highly motivated students usually show better achievement on assigned tasks and tests, resulting in persistence and engagement in those tasks (e.g., Schunk et al., 2014; Zimmerman & Bandura, 1994).

Thus, an understanding of the motivational dynamics underlying math-related behavior allows researchers and educators to better understand how to spark student interest in math-related areas and lead students to embark on the path to math-related career fields. Motivational factors in math are considered important enough for the National Council of Teachers of Mathematics (NCTM) to advance motivational domains among its foremost goals. Example of motivation goals in the NCTM Principles and Standards (1989, p. 99) included ‘learning to value mathematics,’ and ‘becoming confident in one's own ability.’ (Middleton & Spanias, 1999). This dissertation study focused on the predictive roles of math-related motivation beliefs of adolescents explaining math outcomes, especially their intentions to pursue math in the future.

Conceptual Framework

The study drew on Eccles et al.’s (1983) expectancy-value model of achievement-related choices in order to examine the relation between motivational beliefs and willingness to pursue math in the future. The model was initially developed in order to explain the socio-cognitive processes underlying both individual and gender differences in math and science participation (Eccles et al., 1983; Meece, Eccles, Kaczala, & Goff, 1982; Wigfield & Eccles, 1992). The core premise of the model is that the adolescents’ academic choices are predicted by two sets of motivational beliefs: a belief about how well one will do on an upcoming task (i.e., *expectancy for success*) and a belief related to the perceived value of the task with respect to potential costs and benefits (i.e., *subjective task values*) (Wigfield & Eccles, 2002). For instance, if individuals believe that math is interesting or important, these value beliefs influence their academic choices by providing positive meaning to these behaviors. Similarly, when individuals feel confident that they can be successful in math, they are more likely to engage in deeper-level cognitive strategies, leading to an increased academic achievement (Wigfield & Eccles, 1992, 2002). The development of expectancies and task values is influenced directly and interactively by proximal psychological constructs like goals and affective memories as well as by social factors, including cultural milieu in which individuals grow up and socialization agents such as parents, peers, and teachers.

A wealth of expectancy-value research has offered strong empirical support for relations between math-related motivational beliefs and adolescents' math-related choices such as the number and type of courses students choose to take in high school and college (Eccles et al., 2004; Meece, Wigfield, & Eccles, 1990; Nagy et al., 2008). The current study incorporated four existing motivational belief constructs—*math ability belief*, *math interest*, *math utility value,* and *math anxiety*— and a set of hypotheses that each motivational constructs has a direct and unique association with the intention to pursue math in the future within the expectancy-value model. The relations are presented in more detail in Chapter 2.

Statement of Problem

To gain a more comprehensive understanding of the connection between motivational beliefs and willingness to pursue math in the future, the current study addressed and attempted to resolve three limitations of the extant expectancy-value research. These limitations include a lack of consideration of (a) the mediating role of math performance in Eccles et al.'s expectancy-value model, (b) generalizability of the model across cultures, and (c) measurement invariance of scales that measure motivation constructs.

Understanding a Potential Role of Math Performance

How well students perform in math in high school has been described as a significant pathway to educational planning and intention (Middleton & Spanias, 1999). Unfortunately, the influential role of the math performance in explaining the relation between motivational beliefs in math and intention to pursue math in the future is neither well-explored by original Eccles et al.'s (1983) model nor studied in subsequent work.

Adolescents in high school have already made implicit decisions about whether or not they will pursue advanced mathematics and science courses in the future, and these choices are often determined by success in math (Singh, Granville, & Dika, 2002). In general, grades or test scores serve as objective feedback about realistic prospects for success in the field (Schneider & Stevenson, 1999). Thus, low math test scores at the high school level often become the first major academic and psychological barrier against the student's likelihood of choosing and staying in STEM-related majors, which ultimately lowers their possibility of getting into STEM-driven careers (e.g., Berryman, 1983; Riegle-Crumb, King, Grodsky, & Muller, 2012). Given that the influence of motivational beliefs on math achievement is well-established in the literature (e.g., Wentzel & Wigfield, 2009; Zimmerman & Schunk, 2011), it is quite surprising that there is no clear understanding of how motivational beliefs and math performance, taken together, may factor into a student's willingness to pursue math in the future. The current study underscores the mediating role of math performance with respect to the pathways between motivational beliefs in math, math performance, and intention to pursue math in the future.

Bringing Culture into the Conversation

Although numerous studies have validated the Eccles et al. model, these studies have failed to address the generalizability of the model applied to culturally diverse sample. The expectancy-value model has been widely applied to U.S students, and to a lesser extent, to student samples in Canada, Australia, and Germany (e.g., Nagy et al., 2008; Watt, Eccles, & Durik, 2006; Watt et al., 2012). Little is known about the utility of the expectancy-value model for explaining variations in academic outcomes in non-Western populations, especially for East Asian students who tend to excel in tests of mathematics and science. In other words, the functional effects of motivational belief constructs, which are emphasized in the expectancy-value model, have not been widely tested cross-culturally. Indeed, Wigfield, Tonks, and Eccles (2004) mentioned that “much more is needed to look more carefully at the strength of the relations proposed in the model and to see how much they vary across cultures” (p. 191).

Some recent cross-cultural studies have shown that the relation between motivation beliefs and academic behaviors may be more nuanced when examined across nations. For example, research on East Asian students’ motivation reveals that Asian students, who perform relatively high on TIMSS and PISA tests, tend to view their competence in math more poorly than do students in lower-performing countries like the U.S. (e.g., Lee, 2009; Shen & Tam, 2008). Thus, results from East Asian samples are inconsistent with the traditional expectancy-value model: Individuals’ self-beliefs about their ability always predict higher motivation and positive learning outcomes (Wigfield & Eccles, 2002). For East Asian students, low competency beliefs do not necessarily correspond with low academic achievement (Eaton & Dembo, 1997). Because Western and Eastern countries have drastically different value systems that include differences in attitudes, beliefs, and social norms, the current hypothesized model may not work the same way for students in different nations.

Issues on Borrowing Scales for a Cross-National Study

Recent cross-cultural researchers argue that assessing whether an instrument assesses the construct of interest similarly across cultural groups from different cultural backgrounds should be tested before proceeding with substantive analyses such as correlation and predictive paths (Marsh et al., 2013; Niehaus & Adelson, 2013). Douglas and Nijssen (2003) argued that previous cross-national studies might be flawed through the practice of “borrowing scales” developed within on cultural context and applied in different contexts without testing their relevalence and equivalence (p. 621). Testing measurement invariance across groups is essential for accurate interpretations of the construct as well as comparisons between groups in empirically based cross-cultural research (Widaman & Reise, 1997).

There has been surprisingly little previous cross-cultural research that tested measurement equivalence across groups in the education field. Earlier cross-cultural motivation works have assumed, without rigorous evaluation of the construct comparability, that the construct of interest is measured similarly across groups (e.g., Chen & Stevenson, 1995; Eaton & Dembo, 1997; Zusho, Pintrich, & Cortina, 2005). Thus, the findings from these studies are limited and inconclusive because observed differences in the constructs might result from a differential functioning of an instrument, rather than reflecting genuine group differences (Byrne, 2012).

Research Aims

The ultimate purpose of this study was to examine the differences and similarities in the relations between the motivational beliefs (i.e., *math ability belief*, *math interest*, *math utility value*, and *math anxiety*), math performance, and intentions to pursue math in the future. *Intentions to pursue math in the future* are represented by taking additional math classes and putting more effort into math. This study added to existing expectancy-value literature by providing a portrait of how the relations between motivational beliefs and math intentions are understood across cultures within Eccles et al.'s (1983) expectancy-value model. The study achieved this purpose through the following goals. First, this study extended the original Eccles et al.'s (1983) model by including the potential mediating role of math performance in understanding the relation between motivational beliefs and intention to pursue math in the future. More specifically, the extended model includes an estimate of the direct effect between motivational beliefs and willingness to pursue math in the future, as well as of the mediated effect from motivational beliefs to math performance and then to intention to pursue math in the future. Secondly, the study built on the existing literature by exploring whether the hypothesized pathways can be generalized across two cultural contexts: that of the U.S. and South Korea[2]. It examined the relative predictive power of each motivational construct on math performance and intention to pursue math in the future across cultures. Lastly, the study examined the extent to which motivational beliefs measured similarly among U.S. and Korean students. Determining whether a particular construct is measured in the same manner across different groups is essential to a meaningful interpretation of the construct and group comparisons (Milfont & Fischer, 2010).

The study used data from the PISA 2012, an internationally representative dataset widely used for cross-national educational comparisons involving reading, math and science. A proposed model and specific hypotheses for this study are presented at the end of Chapter 2.

Potential Implications of the Study

This study will offer several contributions. It is among the first of its kind to examine whether Eccles et al.'s expectancy-value model can be extended to diverse students, especially those from non-Western cultures. The findings will also provide additional information about the role of motivational beliefs by examining if there is still a unique and direct association between motivational beliefs and willingness to pursue math in the future, even after controlling for the mediating effect of actual math performance level. In addition, the design of the study emphasized the importance of measurement invariance as a prerequisite for comparing scores across cross-cultural groups. Lastly, and perhaps most significantly, the current study will inform teachers, educators, and psychologists about sociocultural forces underlying the relative

[2] PISA collects data from students in South Korean schools. However, the term Korea is used to refer to the sample. In keeping with this practice the current study recognizes the sample location as Korea, rather than South Korea, Hearafter, South Korea is referred to as Korea in the study.

predictive power of each of the motivational constructs in explaining variations in math achievement and math-related choices.

Summary

In summary, this study relied on data from the PISA 2012 to examine relations among motivational beliefs, math performance, and intention to pursue math in the future. In addition, the study examined if, and to what extent, these relations exist across two different cultural contexts. This study was grounded in Eccles et al.'s expectancy-value theory. The findings are expected to inform national educators and policymakers on the importance of understanding the role of math-related motivation in increasing students' intentions to stay in math, which are prerequisite for producing a generation of potentially competitive STEM professionals. This study may serve as a guide for understanding the imperative of implementing strategies that foster math-related motivation in a culturally diverse classroom.

CHAPTER 2: LITERATURE REVIEW

This chapter begins by reviewing the theoretical and research literature on Eccles et al.'s (1983) expectancy-value model of achievement-related choices to show how the current study will contribute to existing literature. Next, I introduce limitations of extant expectancy-value literature. Last, the purpose of the study and the conceptual model are presented (see *Figure 2.2*). Research questions and hypotheses are summarized at the end of this chapter.

Eccles et al.'s Expectancy-Value Model of Achievement Choices

Contemporary motivation theories emphasize the importance of beliefs, values, and goals, referred to as *motivational beliefs*, which explain variations in students' educational achievement and attainment (Eccles & Wigfield, 2002). This study draws on expectancy-value theory developed by Eccles, Wigfield, and colleagues (Eccles et al., 1983; Eccles, Wigfield, & Schiefele, 1998; Wigfield & Eccles, 1992) as its guiding framework. Eccles' expectancy-value model provides one of the most comprehensive theoretical frameworks for studying the psychological and contextual factors underlying both individual and gender differences in math-related motivation, performance, and educational and career choice (e.g., Eccles, 1994, 2011; Eccles & Wigfield, 2002). The current study focuses on the utility of this model in predicting U.S. and Korean adolescents' intentions to pursue math in the future.

Development of Expectancy-Value Model

Eccles and her colleagues' (1983) contemporary expectancy-value theory was developed based on Atkinson's (1957, 1964) expectancy-value model, in which achievement behaviors are hypothesized as determined by *achievement motives*, *expectancies for success*, and *incentive* *values*. Achievement motives are relatively stable and unconscious, and the strength of the achievement motives is derived from the sum of a person's tendency to approach success and to avoid failure (Atkinson, 1957, 1964; Spence & Helmreich, 1983; Wigfield, Tonks, & Klauda, 2009). Besides achievement motives, Atkinson (1957) emphasized the role of expectations for success and the incentive value of success. He defined *expectancies for success* as the expected probability for success on a specific task and *incentive value* as the relative attractiveness of succeeding on a given achievement task. In Atkinson's theory, tasks that individuals believe as difficult and challenging are considered highly valued tasks. Thus, Atkinson proposed that expectancies and values are inversely related so that highly valued tasks are those for which individuals have low expectations for success.

Building on the work of Atkinson (1957, 1964) and Weiner (1985), Eccles and colleagues (1983) proposed a social cognitive model of achievement choice for understanding adolescent performance and choice in the mathematics domain. The model was initially developed to help explain the gender differences in motivational beliefs in mathematics and how these beliefs affect girls' and boys' choices of math-related courses and majors (e.g., Eccles et al., 1983; Eccles, 1984; Meece et al., 1982; Wigfield & Eccles, 1992). Today, the model is applied broadly as a framework for studying the motivational and social factors influencing individuals' allocation of effort, activity choices, and career decisions across a variety of life activities—primarily, those that are achievement based (Eccles, 2011).

In keeping with Atkinson's theory, Eccles et al.'s expectancy-value model depicts achievement motivation as a function of both expectations for success and the incentive value of success. However, Eccles et al.'s model includes several unique features that take it beyond traditional expectancy-value models. First, it elaborated upon both the expectancy and value components. Eccles and colleagues challenged Atkinson's premise that expectancies and values are inversely related and reported a positive relation between the two constructs (Meece, Wigfield, & Eccles, 1990). Secondly, the new model identified developmental sources of children's and adult's expectancy and value beliefs. More specifically, the development of expectancies and task values are influenced, directly and interactively, by proximal psychological constructs (e.g., goals and affective memories) as well as by socialization agents such as parents, peers, and teachers. Most important, for the present study, the Eccles et al. model of achievement motivation emphasized the role of cultural milieu of the developing child.

Directional Processes within Expectancy-Value Framework

The Eccles et al. (1983) expectancy-value theory has elaborated upon the dynamic processes underlying educational and professional choices. *Figure 2.1* depicts a recent version of their model. Here, Eccles et al. linked educational and other achievement-related choices to two broad sets of influences: (a) a set of psychological factors (e.g., expectancies, values, goals, and affective experiences) and (b) a set of social and cultural factors (e.g., socializers' behaviors and attitudes, cultural norms, etc.).

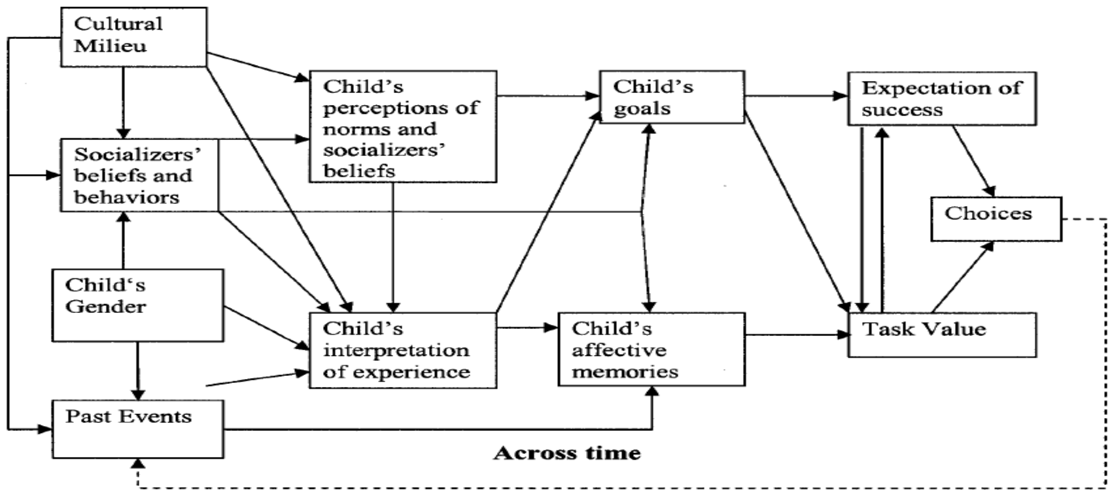

Figure 2.1 Eccles et al. Expectancy-Value Model of Achievement Motivation (The figure is revised from Eccles, 2011, p. 196)

The central idea of the Eccles et al. (1983) model is that children's achievement performance, persistence, and choice of achievement tasks are most directly predicted by their *expectancies for success* in those tasks and the *subjective values* they attach to those tasks (Eccles et al., 1983; Wigfield & Eccles, 1992). As displayed, expectancies and values are influenced by task-specific beliefs and affective memories. Children's task-specific beliefs, which include *perceptions of competence* and *perceptions of the difficulty of different tasks*, and their *goals*, affect the development of an individual's expectancies and values on a particular task. *Affective memories*, reflecting individuals' previous affective experiences with a particular activity or task, influence one's response to similar tasks (Eccles et al., 1983). These beliefs, goals, and affective memories, in turn, are influenced by individuals' perceptions of parents' and teachers' attitudes and expectations for themselves as well as and their interpretations of previous achievement outcomes (Eccles et al., 1983, Eccles et al., 1998; Wigfield & Eccles, 1992). Lastly, individuals' perceptions and interpretations are influenced by a broad array of social and cultural factors. These include socializers' beliefs and behaviors, children's interpretations of their past outcomes (e.g., students' prior achievement), and the broader cultural milieu of the child (e.g., sex-role structure, economic system). Because the model was originally designed to explain gender differences in math-related career choices, Eccles and colleagues focused on gender-role stereotypes or cultural stereotypes about subjects or occupations in their discussion of cultural milieu (Eccles et al., 1983; Meece et al., 1982; Wigfield, Tonks, & Eccles, 2004).

The expectancy-value framework has generated a wealth of research which offers strong empirical support for the relations depicted in the model. Thus, the current study draws on the expectancy-value framework from which (a) the main motivation constructs are derived and (b) the relation between these motivational constructs and academic outcome variables (i.e., math performance and intention to pursue in math in the future) are examined.

Key Motivational Belief Constructs Examined in the Study

Because the main focus of the study was to explain the unique role of math-related motivation in predicting math-related achievement and choices, attention is directed to four of the most proximal psychological components mainly drawn from the expectancy-value framework: *math ability beliefs, math interests, math utility values,* and *math anxiety*. Previous theoretical and empirical studies indicated that these motivational belief constructs were conceptually distinct and so each was presumed to serve a distinct function in explaining individuals' behaviors in math-related areas (e.g., math course enrollment, math-related career choice, or intention to pursue in math in the future). Each component is discussed below under the expectancy-value framework.

Ability-Related Belief Component

Eccles and her colleagues' (1983) expectancy-value model highlights the roles of *expectancy for success* and *subjective task values* as the most immediate or direct predictors of achievement performance and choice. First, they defined *expectancy for success* as an individual's belief about how well he or she will perform on an upcoming task (e.g., how well do you think you will do in math next year?). Expectancy for future success is largely determined by students' *ability beliefs*, also referring to as *ability self-perceptions* or *ability self-concepts*, which are defined as students' evaluations of their current competence in a given domain (Wigfield & Eccles, 2000). These beliefs are typically revealed in self-reports which allow individuals to rate their performance in certain tasks (e.g., how good in math are you?) as well how they think they compare to other students.

Conceptually, ability beliefs are distinguished from expectancies for success, as ability beliefs focus on present ability, whereas expectancies for success focus on the future (Wigfield & Eccles, 2000). However, previous studies showed that expectancy for future success and ability beliefs are highly related and empirically indistinguishable (e.g., Eccles, Wigfield, Harold, & Blumenfeld, 1993; Wigfield & Eccles, 2000). Thus, I employed *math self-concept* (Marsh, Walker, & Debus, 1991), which refers to a belief about one's ability in math, as an indicator of ability belief and expectancy belief in the current study.

Among ability-related constructs developed across different theoretical perspectives, the conceptual definition of *self-concept* is the most similar to Eccles et al.'s *ability belief*. The concept of self-concept focuses on evaluation of competence in a specific achievement domain (Wigfield & Eccles, 2000) and is heavily influenced by social comparison (Bong & Clark, 1999). Like those of ability beliefs and expectancies, measures of self-concept have tended to be domain- rather than task-specific. The target of this approach is broader than that of Bandura and other researchers studying self-efficacy (see Wigfield & Eccles, 2000). In contrast, Bandura (1997) conceptualized *self- efficacy* as a judgment of one's capabilities to execute particular behaviors in specific situations and is measured by context-specific assessments of competence to perform a task.

Task Value Components

In the Eccles et al. (1983) model, *task values* are assumed to be qualities of the task or activity that contributes to the increasing or declining probability that an individual will select it. These values are believed to be subjective because various individuals assign different values to the same activity. More specifically, Eccles and colleagues define subjective task values as how a task meets the different *needs* of individuals (Eccles et al., 1983; Wigfield & Eccles, 1992). The model includes four components of subjective task value: attainment value, intrinsic value, utility value, and cost (Eccles & Wigfield, 1995). First, Eccles and colleagues defined *intrinsic or interest value* as perceived enjoyment the individual gets from doing the activity. They argued that an individual is likely to be intrinsically motivated to do the task when a task has high interest value. Second, they defined *utility value* as perceived usefulness of the activity for obtaining one's goals such as career goals. If individuals perceive tasks as being instrumental in fulfilling future goals, they might pursue the tasks even though they are not interested in these tasks for their own sake. Third, *attainment value* included perceptions of the perceived importance of being well at an activity. Tasks are considered as being important "when individuals view them as central to their own sense of themselves, or allow them to express or confirm important aspects of self" (Wigfield & Cambria, 2010, p. 4). The last value component is the *cost* of engaging in the activity, referring to what individuals are willing to give up for participating in a task. Individuals might not choose a task if they perceived that the costs in terms of the effort, time, or energy required are too great. Empirically, higher task values lead to more focused attention, persistent effort, increased cognitive and affective functioning, so as to higher achievement and choices (Ainley, Hidi, & Berndorff, 2002; Wigfield & Eccles, 2000).

Most empirical studies have focused on the first three of these constructs (Wigfield & Eccles, 1992). In the current study, I included *math interest* and *math utility value* to represent the constructs of task values. *Math interest* refers to students' attraction to, liking of, and enjoyment of math. In general, task valuation extends beyond task enjoyment: students also engage in tasks that have utility value and attainment value. Within achievement domains where competent performance is salient, utility value and attainment value are not distinguishable or even can merge (Durik, Vida, & Eccles, 2006; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). Consistently, prior research on achievement task values revealed a strong relation between utility value and attainment value. Thus, instead of including both utility value and attainment value as separate constructs, I employed *math utility value* that refers to the practical significance of a math-related task (i.e., how it can be instrumental in fulfilling their future studies and careers, Wigfield & Eccles, 1992) in the current model.

Relation between Ability and Value Constructs

Contemporary expectancy-value theory assumes positive relations between ability beliefs and task values (e.g., Eccles et al., 1983; Meece et al., 1990). This assumption contrasts with Atkinson's (1957) assumption that the most difficult tasks for individuals to perform (i.e., tasks on which individuals have low expectancies for success) are perceived as the most valued. Eccles et al. (1983) argued that children are more likely to value activities on which they do well, and those beliefs then begin to mutually predict performance and choice of different activities.

A number of empirical studies support these positive associations between self-concept and task value. For example, Eccles and Wigfield (1995) found that children's competence beliefs in math are strongly associated with their interest and perceived importance of math. Meece et al. (1990) also reported positive bidirectional relations between expectancies and values and showed these positive association leading to an indirect effect of value constructs upon achievement outcomes (e.g., value constructs are indirectly associated with performance via ability belief). Jacobs et al. (2002) further reported that adolescents' changes in competence belief explain a large portion of their changing values in particular domains, arguing for links between achievement-related beliefs within the self-system that closely influence each other.

Anxiety Component in Expectancy-Value Model

In addition to ability beliefs and task values that emphasize cognitive aspects of motivation, I includeed *math anxiety* as a construct that represents an emotional aspect of motivation in the current study. Math anxiety has often been considered a subject-specific manifestation of anxiety (e.g., Bandalos, Yates, & Thorndike-Christ, 1995; Hembree, 1990; Ho et al., 2000; Meece et al., 1990). It includes negative affect reactions to math including feelings of nervousness and tension, and cognitive concerns about test taking and performance (Wigfield & Meece, 1988). Early studies identified math anxiety as a promising motivational construct for understanding avoidance behavior in mathematics (e.g., Tobias, 1978; Llabre & Suarez, 1985). As Tobias and Weissbrod (1980) stated, "[math anxiety] inhibits work because in order to avoid the anxiety the student will stop studying mathematics" (p. 65). Math anxiety has been considered a critical psychological factor which generally threatens math performance and leads to avoidance of mathematics.

Within the original Eccles et al. expectancy-value model, anxiety and other emotions were not explicitly included. Rather, the model included emotions related to past learning activities, which are labeled *affective memories*. Atkinson's (1964) motivation theory highlighted *motives* such as the motive to approach success or to avoid failure. Motives were considered affective by nature and representative of learned but stable individual differences (Covington, 1992). *The motive to approach success* reflected individuals' capacity to experience pleasure and pride in obtaining a goal, while *the motive to avoid failure* represented the anticipation of shame or fear if one cannot obtain the desired goals. Regarding anxiety, Akinson (1964) considered "the strongest anxiety about failure" as being "the maximum strength of avoidant motivation" (p. 52). Comparatively, Eccles et al. (1983) emphasized a social-cognitive view of achievement motivation. Thus, the model did not adapt personality dispositions such as fear of failure. Rather, Eccles and colleagues included achievement-related emotions (e.g., pleasure, satisfaction, fear of failure, and anxiety) as a part of the *affective memories* component. Positive or negative affective memories are associated with past participation in a specific task or activity and affect individuals' responses to similar tasks in future. For example, if children have had bad experiences with math teachers in the past, they are likely to feel less positive toward mathematics, resulting in reduced participation in math-related tasks.

In the Eccles et al. model, the role of math anxiety was explained in terms of task values (i.e., perceptions of the value in math). In other words, math anxiety was reflected in the value of a perceived learning opportunity (Eccles, 2005) and contributed to either encourage or discourage the individual from engaging in that learning opportunity (Gorges & Kandler, 2012). More specifically, Eccles and her colleagues discussed anxiety in terms of the *cost* of engaging in different tasks. All individuals' choices are assumed to have associated costs and individuals do not choose a task when they perceive that the costs of participating are too great (Eccles, 2011). In general, cost was conceptualized in terms of all of the negative aspects of engaging in the task (Eccles et al., 1983; Eccles, 1987). It included anticipated emotional states (e.g., fear of both failure and success) as well as the amount of effort that will be required to succeed at the task. Thus, the anticipated anxiety of engaging in a math-related activity is highly related to an individual's beliefs related to the *cost* of participating in the activity (Eccles et al., 1983). Individuals are less likely to continue in mathematics when they believe that engaging in math-related activities will bring high levels of anxiety generated from negative affective memories of past experiences. Students are more willing to invest their effort when activities are affectively positive and interesting rather than anxiety-laden or boredom-inducing (Frenzel, Pekrun, & Goetz, 2007).

Assuming that math anxiety is understood as a component of task values, how then may the relation between ability confidence in math and math anxiety be explained in the expectancy-value framework? Fennema and Sherman (1979) argued that math anxiety may simply represent low confidence due to a very high correlation (r = -.89) between high school students' math anxiety and math ability concepts. Similarly, expectancy-value studies document a strong negative correlation between anxiety and ability beliefs such as self-concept or self-efficacy (see Hembree, 1990 for a review of math anxiety). However, researchers maintain these constructs are theoretically and empirically distinct from each other (Jain & Dowson, 2009; Lee, 2009; Wigfield & Meece, 1988). Specifically, Wigfield and Meece (1988) argued that anxiety represents "more than a lack of confidence in math; rather, it also centers on negative affective reactions to math" (p. 214). In other words, it should not be assumed that building individuals' confidence always results in reduced negative affective states.

Emotionality is the affective component of anxiety, including feelings of nervousness, tension, fear, and negative physiological reactions to a situation or a task. *Worry* is the cognitive component of anxiety, manifested as negative expectations and self-deprecatory thoughts about a situation or task (Morris, Davis, & Hutchings, 1981; Sarason, 1986; Wigfield & Meece, 1988). These two components of anxiety are empirically distinct even though they are correlated (Morris et al., 1981; Wigfield & Meece, 1988). Regarding math anxiety, the worry component is most likely to be correlated with low math ability beliefs because it focuses on cognitive concerns for performing well in mathematics (Wigfield & Meece, 1988). The emotionality component might not appear to be significantly related with low math ability beliefs. Thus, for math-anxious students, efforts focused on improving confidence in math- related situations may be effective in reducing concerns about low performance in math. However, such efforts might not be effective in eliminating fear or dread of math. Based on these findings, the current study assumed that math anxiety was conceptually and empirically distinguishable from other motivational constructs (i.e., ability belief or other task value constructs) and it was directly associated with students' math-related choices (see *Figure 2.2*, p. 41).

Relation between Motivational Beliefs and Intention to Pursue Mathematics

Importance of Intention to Pursue Mathematics in the Future

Because each educational choice in adolescence serves as a predictor of adult life experiences (Schoon et al., 2002), the predictive relation between motivational beliefs and adolescents' academic choices has been of great interest to motivation researchers (Schunk et al., 2014). According to the Eccles et al.'s expectancy-value model, achievement-related choices, whether made consciously or unconsciously, are guided by individual's expectations for success for various options, and the value the individual attaches to the various options at the time. Individual choices are determined after considering the pros and cons of available options in terms of their ability as well as considering which choice reasonably maximizes their personal value (Eccles, 2005; Wang & Degol, 2013). For example, even though children feel competent on math, they would not choose to pursue coursework in math if they perceive that the costs in terms of the effort required are too great and not in line with their utility value.

In the current study, *intention to pursue math in the future* was employed as a dependent variable because it is a representative indicator of important choice-related behaviors in adolescence. Eccles and colleagues assumed that educational choices reflect a long series of choices along an educational pathway (Eccles, Vida, & Barber, 2004). Adolescence is a time of increased freedom to make academic choices. Students are given more freedom in course selection, which influences their school curricular track, and they develop career preferences that will affect their options for college and potential careers (Eccles, Adler, & Meece, 1984; Eccles et al., 2004). Especially, during high school, students are making a choice of whether to stay in the math stream (Crombie et al., 2005). Intention to pursue math in the future is one of the conscious choices that students make. It is defined as an individual's desire or willingness to purse math-related choice behaviors (e.g., enrollment in advanced mathematics, level of applied effort in math, or selection of math-related college majors).

Understanding adolescents' intention to pursue a target task or behavior in the future has been underscored by researchers because it is the most significant predictor of actual decisions in the future in previous studies (e.g., Eccles et al., 2004; Rojewski, 2005). Studies indicated a strong, positive relation between the plans of early adolescents and their educational decisions down the road. For example, Eccles, Vida, and Barber (2004) examined longitudinal relations between six-graders' intentions to enroll in college and enrollment patterns six year later. Sixth-graders who were more certain about their college plans were more likely, than less certain peers, to have higher GPAs, to enroll in college-track mathematics courses during high school, and to attend college full time. These relations were identified even when sixth-grade mathematics performance was included as a control variable. Given these relations, the intentions of adolescents to pursue math is an important academic outcome to consider for understanding math-related educational or career options (Eccles et al., 2004).

Motivational Beliefs Influencing Intention to Pursue Mathematics in the Future

In the expectancy-value model, students' expectancies for success and task value directly predicted their performance as well as choices of which activities to do (Eccles et al., 1983). A number of empirical expectancy-value studies have examined the relations between math-related motivational constructs (e.g., expectancy of success, math values, etc.) and intention to pursue math in the future (e.g., Gainor & Lent, 1998; Meece et al., 1990; Waller, 2006; Wigfield & Eccles, 2000). These studies examined the unique predictive utility of each of the motivation constructs in predicting enrollment intentions or actual choices. Contrary to hypothesized predictions, students' expectancies for success in math did not often play as strong predictors of intention to pursue math. Instead, the findings consistently emphasize importance of math-related values for predicting educational choice-related behaviors. For example, Meece et al. (1990) identified a strong, direct, and positive relation between self-reported importance of math and intentions to take more math; relations between performance expectations and enrollment intention were not significant. Similarly, Eccles et al. (2004) found that sixth-grade youth's own academic values (i.e., importance placed on math and English) were powerful predictors of their college plans. In contrast, the same students' academic self-concepts related to math and English were less predictive of their college plans. In another study, Updegraff, Eccles, Barber, and O'Brien (1996) examined the roles of three psychological constructs (i.e., self-concept of ability in math, utility of math, and interest in math) as predictors of high school math course enrollment; the perceived utility value of math was the strongest and more consistent predictor of math course enrollment for both boys and girls. Taken together, previous expectancy-value studies have consistently shown that task values have their strongest direct effects on choices, whereas ability beliefs as having the strongest direct effects on performance (e.g., Denissen, Zarrett, & Eccles, 2007; Durik et al., 2006; Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005). When indicators of task values were entered into structural equations, ability beliefs were likely to have less independent predictive power in predicting course enrollment plans and actual course enrollment. Rather, as discussed earlier, due to strong relation between ability beliefs and value beliefs (Eccles & Wigfield, 2002), value constructs apprear to have indirect effect on math intention via the ability beliefs (e.g., Meece et al., 1990). Few expectancy-value studies have examined the independent contribution of math anxiety on choice intention, above and beyond the effects of other motivational belief constructs. Meece et al. (1990) examined the relative influence of performance expectancies, value perceptions, and math anxiety on course enrollment intentions in math. They reported that math anxiety did not have a significant direct effect on course enrollment intentions. Its relation to course enrollment was through expectancies and values. This finding suggested ability beliefs and task importance were stronger predictors of course enrollment intentions when compared with the predictive value of math anxiety. However, the findings must be replicated with other samples. Other studies have uncovered strong relations between math anxiety and the tendencies of students to avoid mathematics (e.g., Betz, 1978; Felson & Trudeau, 1991; Hembree, 1990). High-math anxious students are more likely to have negative attitudes toward mathematics-related activities, to take fewer school mathematics courses, and to show less intention in high school and college to take more mathematics (see Hembree, 1990, for a review of math anxiety).

In summary, numerous studies have examined the relations between expectancy constructs and/or value constructs and math enrollment intentions. However, these relations are still not completely understood. Thus, an important purpose of this study was to reexamine the relative contribution of each motivational construct to intentions to pursue math in the future.

Remaining Issues of Prior Research

Researchers suggested a number of issues that need further consideration. This section presents several issues that have influenced on the development of the extended framework and resultant research hypothesis which were employed in the current study.

The Role of Current Math Performance Level

Like choice-related variables, including math course enrollment or intention to pursue math in the future, current math performance was generally treated as an outcome variable in previous expectancy-value studies. One important issue left unresolved is the meditation role of current performance in explaining the relation between adolescents' motivational beliefs and choice-related intention, such as course enrollment intention or major selection intention. Achievement in a particular domain helps to shape educational and career aspirations. For example, current math performance level often work as objective and realistic evidence for determining whether students will pursue math-related activities in the future (Gottfredson, 1981; Lent, Brown, & Hackett, 1994; Singh, Granville, & Dika, 2002). Singh and colleagues (2002) reported that adolescents in high school have already made implicit decisions about whether they will pursue advanced mathematics and science courses in a college, and these choices were informed by their experiences of success in math. In addition, children who earn good grades in math and science are more likely to participate in after-school activities and continue with coursework in these areas in the future (Simpkins, Davis-Kean, & Eccles, 2006).

The original expectancy-value model posited that expectancy and value constructs were directly related to children's choice of achievement tasks (Eccles et al., 1983; Wigfield & Eccles, 2000). For a more comprehensive understanding, it is necessary to extend the original model by including math performance as a mediator for explaining the relation between motivational belief constructs and intention to pursue math in the future. In the proposed study, each of the motivational belief constructs were predicted to have a direct and positive relation to adolescents' math performance. In turn, mathematics performance was hypothesized as positively related to intention to pursue math in the future. In other words, high math self-concept, interest, and utility value, and low math anxiety may increase math performance, leading to stronger intentions to pursue math in the future (see *Figure 2.2*).

These hypothesized relations between motivational beliefs and math performance are supported by a number of empirical studies that found: there is a strong and positive relation between math competency beliefs and actual performance in mathematics (e.g., Hackett & Betz, 1989; Pajares & Miller, 1994; Marsh, Walker & Debus, 1991) and between math interest and math achievement (e.g., Köller, Baumert & Schnabel, 2001; Simpkins et al., 2006; Wigfield et al., 1997). For example, Spinath, Spinath, Harlaar, and Plomin (2006) reported that children's math ability self-perceptions and the intrinsic values they find in math both contribute incrementally to the prediction of achievement, with ability self-perceptions being a better predictor than intrinsic values. In addition, mathematics achievement is negatively correlated with math anxiety (e.g., Ma, 1999; Satake & Amato, 1995; Zakaria & Nordin, 2008). The hypothesized positive relation between math achievement and math intention is also supported by prior studies (e.g., Singh et al., 2002; Simpkins et al., 2006).

Issue of Generalization of the Expectancy-Value Model across Cultures

A particular limitation of prior achievement motivation research is the limited comparative research in cross-cultural settings (Elliott & Bempechat, 2002; Wang & Degol, 2013; Wigfield et al., 2004). The scarcity of research in this area implies that a Western model of achievement motivation has been criticized as being culturally entrenched in an ideology of individualism (Otsuka & Smith, 2005). To date, most findings in expectancy-value studies have been derived primarily from studies conducted among students in the United States (Wigfield et al., 2004). Only recently have expectancy-value studies been conducted outside of North American contexts, such as Australia, Canada, and Germany (e.g., Nagy et al., 2008; Watt, Eccles, & Durik, 2006; Watt et al., 2012). The results showed that relations between motivational beliefs and academic choices are generally similar across countries. However, several cross-cultural differences in relations were identified. For example, Watt, Eccles, and Durik (2006) found that the processes of academic-related choices appear to be highly similar across the cultural settings of Australia and the United States. They found that for U.S. students, each motivational belief (i.e., math self-concept, math interest, and math importance value) was shown to influence adolescents' choices for participation in math activities. Similar patterns emerged among Australian students. Notably, math interest displayed a stronger direct relation to Australian adolescents' choices for math participation compared with math self-concept or prior math achievement. Watt et al. (2012) compared Australian, Canadian, and U.S. adolescents and found utility value to be one of the most significant predictors of senior high math course choices, regardless of nationality. In addition, intrinsic value was only found to positively predict math course choices among the Australian samples. In contrast, positive relations between expectancy for success and math course choices emerged among the U.S. and Canadian adolescents. Thus, different motivation beliefs informed enrollment decisions for Australian, Canadian, and U.S. students.

Although some interesting similarities and differences across countries emerged, these findings have not been extended to non-Western samples, specifically to East Asian cultures such as those of China, South Korea, and Japan. So for now, existing findings should be interpreted with caution, as the cultural divides severely restrict generalizability beyond Western individualistic cultures (e.g., Australia, Canada, or Germany). These Western countries may differ from one another in many respects, but they also share many features including a common language, aspects of the school curriculum, and value systems —patterns of attitudes and beliefs (Nagy et al., 2008; Triandis, 1996).

The scarcity of research focusing on non-Western countries is problematic for two reasons. First, additional studies are needed to examine whether the relations conceptualized in the expectancy-value model can be appropriately applied across cultures. Wigfield, Tonks, and Eccles (2004) argued that the expectancy-value model is "particularly well suited for a cultural analysis of motivation and activity choices" (p. 169). They assumed that many, if not all, of the links proposed in the expectancy- value model would also be found in Asian collectivistic cultures. They also argued that although the directional paths are equivalent across cultures, the relative predictive power of each of the motivational constructs in explaining adolescents' academic choices could vary across cultures. Unfortunately, these arguments have been rarely tested with empirical evidence. In addition, relations between motivation-related beliefs and academic behaviors appear to be more nuanced when examined across nations. For example, research on the relation between the achievement of East Asian students and their self-competence in math revealed that East Asian students, who perform relatively high on TIMSS and PISA tests, tend to view their competence in math more poorly than do students in lower-performing countries such as the U.S. (e.g., Lee, 2009; Shen & Tam, 2008). These results from the East Asian student samples are inconsistent with findings based on Western samples: positive self-perception of ability should lead to more positive learning outcomes (Wigfield & Eccles, 2002).

Because Western and Eastern countries have drastically different value systems that include a variety of attitudes, beliefs, and contexts, the original Eccles et al.'s model may be less valid when applied to East Asian students. In East Asian countries, the development of motivational beliefs and academic choice behaviors is deeply influenced by collectivistic-Confucian tradition. Generally speaking, individualistic cultures, such as that of the U.S., emphasize personal accomplishment (Triandis, 1996) and individual behavior within these cultures is regulated by one's own needs or goals (Triandis, McCusker, & Hui, 1990); feeling good about oneself is highly valued (Oyserman, Coon, & Kemmelmeier, 2002; Triandis, 1996). In contrast, under collectivistic cultures, one's behavior is regulated by the norms and values of the group, such as the family or community. Under these cultural contexts, East Asian adolescents are discouraged from sharing and boasting their accomplishments and abilities to others (Markus & Kitayama, 1991). Significant others, such as parents, teachers, and peers, play important roles in determining individuals' behaviors.

Additionally, academic excellence is considered among the primary values of East Asian students (Bempechat & Drago-Severson, 1999). Thus, when children fail to produce satisfactory results, they often suffer guilt and a sense of failure, believing that by failing to fulfill their obligations they have brought shame to their families (Hong, 2001). This cultural expectation of high achievement is also highly related to the environment of East Asian school systems. East

Asian high schools are characterized as controlling, competitive, and academically demanding (Park & Kim, 2014). Particularly, during the middle-to-high-school transition, most East Asian adolescents experience strong pressure towards academic success and a heightened sense of competition while preparing to apply to top universities (Kim & Byun, 2014). These differing cultural norms and expectations and differently structured educational systems may lead to distinctive patterns of motivation as well as the relations between motivation, academic achievement, and activity choices of adolescents from Western and Eastern countries.

Understanding expectancy-value model in Asian contexts[3]. There are few prior studies that address East Asian students' motivation and its role in predicting academic activities. As Wigfield et al. (2004) argued, more expectancy-value work is needed to identify the cultural forces (i.e., Western vs Eastern) that underlie mean-level differences in ability beliefs and task values,and determine the relative predictive power of these constructs on predicting the various achievement-related intentions or choices available to the individuals.

With regard to the mean-level comparison of the four motivational beliefs employed in the study, several studies were conducted to compare students from the Western countries with those from the East Asian countries. These studies have consistently reported that East Asian students exhibit lower math self-concept (e.g., Eaton & Dembo, 1997; Shen & Pedulla, 2000) and higher fear of failure (e.g., Ho et al., 2000; Zusho, Pintrich, & Cortina, 2005) than their Western counterparts. Stankov (2010) has argued that Confucian Asians are more anxious and

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[3] One of the challenges in conducting a cross-cultural study is whether or not to consider students within one culture as one homogenous population. Certainly, each country is made up of individuals with diverse backgrounds and positions in the social structure so that there is within-national variation—e.g., age, gender, ethnicity, and socioeconomic status— in each country. In this dissertation, in order to reduce the impact of within-country variation in explaining between-country difference of motivation and math-related outcomes, I included age, gender, and socioeconomic status as control variables in the analysis.

self-doubting (i.e., they are less confident about their abilities) than their European peers due to familial and societal pressures placed upon them to achieve academically. A limited number of studies reported compararable levels of math interest and importance for East Asian and Western students. For example, Sun, Ding, and Chen (2013) found that Chinese (*N* = 806, 8 schools) and American (*N* = 813, 14 schools) middle school students equally appreciated the intrinsic value of education, but Chinese students showed stronger utility values of education than their American peers. However, study design differences, including the measures of values utilized, the representativeness of the samples, and subject areas considered, limit the generalizability of these findings.

There have been very few cross-cultural studies that examine the relations between motivational beliefs and math-related intentions as well as math performance. The positive relation between math self-concept and math performance previously mentioned was replicated in several cross-cultural studies (Marsh & Hau, 2004; Shen & Pedulla, 2000; Shen & Tam, 2008). Marsh and Hau (2004) validated the generalizability of a pattern of positive relations between math self-concept and math achievement across 26 countries, including the U.S. and Korea, using PISA 2000 data. Three studies reported that math interest and importance were identified as stronger predictors of academic achievement than ability beliefs among East Asian students (Eaton & Dembo, 1997; Pualengco, Chiu, & Kim, 2009; Zusho et al., 2005). However, the findings were limited because they were restricted to Asian Americans (e.g., Eaton & Dembo, 1997) or relied on data from very small samples (e.g., Pualengco et al., 2009; Zusho et al., 2005).

Based on Wigfield et al.'s (2004) argument, the current study assumed that the hypothesized relations between motivational beliefs in math, math performance, and intention to pursue math in the future would be present in East Asian cultures, specifically for Korean students, in a consistent way. At the same time, variations in the strength of these relations were expected. As discussed earlier, East Asian cultures emphasize the *valuing of achievement* rather than beliefs about one's ability. East Asian children are assumed to have internalized values relevant to achievement more strongly than American children. Thus, the current study assumed that Korean students are more likely to have stronger direct relations between value constructs (i.e., math interest and math utility value) and intention to pursue math in the future, and between the former and math performance, when compared with American students.

Measurement Equivalence of Constructs across Cultures

In order to examine the generalizability of the model across cultures, the current study employed a *cross-cultural approach* as comparing students who live in different countries. Cross-cultural research is typically divided into two distinct approaches. First, an *etic approach* to cross-cultural research assumes that psychological constructs have the same meaning across cultures and these are universal constructs. In contrast, an *emic approach* assumes that psychological constructs are differently characterized within the specific context (see Wigfield et al., 2004). This study employed an etic approach based on the empirical evidence on universal existence of self-concept in math, math-related values, and math anxiety across cultures (e.g., Bong, 2001; Henderson, Marx, & Kim, 1999). In other words, the study assumeed that each motivational belief is seen as a core element in the basic psychological mechanisms of adolescents regardless of cultural contexts and the relative degree of each motivational belief should be differentiated across cultural contexts.

To make it possible to conduct an etic approach for cross-cultural comparison, instruments employed must measure the same psychological construct in all groups. That is, testing whether an instrument measures the construct of interest similarly for members of different cultures is an essential prerequisite before proceeding with substantive analyses (e.g., correlation and predictive paths) or mean-level comparisons. However, assessments regarding the extent to which motivational beliefs measures are equivalent across cultures is a relatively recent phenomenon (Marsh et al., 2013; Niehaus & Adelson, 2013). Earlier cross-cultural motivational works (e.g., Chen & Stevenson, 1995; Eaton & Dembo, 1997; Sun et al., 2013) just assumed the construct comparability without rigorous evaluation. In most prior comparative studies, adolescents simply had to respond to investigator-generated items, generally created by Western researchers and then translated (Bempechat, Jimenez, & Boulay, 2002). Findings from these studies were limited and inconclusive because observed differences in the constructs might result from a differential functioning of an instrument, rather than reflecting genuine differences (Byrne, Shavelson, & Muthén, 1989). Thus, measurement invariance should be tested in cross-cultural studies.

There are several advanced methodological approaches to test measurement invariance. Recently, measurement invariance is widely tested within the framework of structural equation modeling (SEM). The technique is a robust procedure for investigating equivalence in multi-group data due to its ability to assess whether each observed indicator is related to a latent variable in the same way in all groups (Milfont & Fischer, 2015). In addition, a SEM approach makes it possible to investigate the direct and indirect relations among the variables across cultures simultaneously (Byrne, 2012).

There have been several but limited motivational studies employing SEM approaches to examine issues of measurement equivalence (e.g., Chirkov & Ryan, 2001; Levesque, Zuehlke, Stanek, & Ryan, 2004; Ryan et al., 1999; Wang & Guthrie, 2004). Most of these studies were designed in the framework of self-determination theory, positing that autonomy, competence, and relatedness (each representing a basic psychological need) are essential in promoting life satisfaction and well-being (Deci & Ryan, 1985). For example, Levesque et al. (2004) conducted invariance analyses to support the cultural comparability of latent constructs (i.e., autonomy and competence) across Germany and the U.S. and then concluded that German college students felt significantly more autonomous and less competent than American. To date, there has been no study to examine cultural comparability of expectancy and value constructs within the framework of expectancy-value theory.

The current study employed the *mean and covariance structure analysis* (MACS; Little, 1997) that has been utilized in several cross-cultural motivation studies (e.g., Chirkov & Ryan, 2001; Levesque et al., 2004). MACS approach is a variation on traditional SEM; it directly tests the measurement equivalence of constructs by utilizing both latent means and covariance structures of the data. Main theoretical and methodological issues related to MACS are discussed in detail in the Chapter 3.

Purposes of the Study

Based on limitations of previous studies discovered, the study proposed to extend the conceptual model of Eccles et al.'s expectancy-value theory (*Figure 2.2*). Grounded in the model, the central aim of the present study was to explore the relations between motivational belief constructs and willingness to pursue math in the future, with focus on the mediating role of current math performance. The present study delved more deeply into unique influence of various motivational constructs in explaining adolescents' academic choice, with the goal of providing insights into the accumulation of knowledge in the expectancy-value model of achievement motivation. The second aim of the current study was to examine the moderating role of culture in understanding these relations. The present research investigated cultural similarities and differences in the strength and/or presence of relations among motivational belief constructs, math performance, and intention to pursue math in the future in a sample of 15-year-old U.S. and Korean adolescents. In addition, the study examined the mean differences in each of motivational beliefs across the Korean and U.S. samples. This cross-cultural approach bridges the gaps left by previous research, with respect to the generalizability of the model in a diverse sample. Particularly, in order to enhance the rigor of multigroup comparison analysis, the study considered the issue of measurement invariance. The assumption that instrument measures the same psychological construct in all groups was tested using a MACS approach.

Model Specification

Figure 2.2 presents a pictorial summary of the proposed conceptual model of mechanisms. Acknowledging the limitations of previous research, the proposed study expanded the original Eccles et al.'s expectancy-value model. Each feature of the model is described in more detail below. Because of the cross-sectional data used in the study, it should be kept in mind that analyses tested only for relations among constructs. Thus the model testing procedures do not provide a basis for causal inferences (Hoyle, 1995).

The model included four different motivational constructs as independent variables in order to demonstrate adolescents' motivational tendencies in mathematics: math self-concept, math interest, math utility value and math anxiety. First, *math self-concept* is defined as students' beliefs in their own mathematics ability (Marsh, Walker, & Debus, 1991). Next, *math interest* and *math utility value* represent the constructs of task value component (Eccles et al., 1983). Math interest refers to students' attraction to, liking of, and enjoyment of math, and math utility refers to the drive to learn mathematics because students perceive it as useful to them and to their future studies and careers (Wigfield & Eccles, 1992). Lastly, *math anxiety* is a negative emotion that interferes with the solving of mathematical problems (Llabre & Suarez, 1985). Each of the four motivational constructs was assumed to be correlated in the model. There strong associations between constructs have been consistently reported in prior empirical studies (e.g., Eccles & Wigfield, 1995).

Based on the theoretical and empirical prior studies reviewed above, the model posits that motivational beliefs are associated with intention to pursue math in the future directly and indirectly via current math performance level. The model assumed that there would be a unique and direct association between motivational belief constructs and intention to pursue math in the future even after controlling for the mediating effect of actual math performance level.

Specifically, in the proposed model, I hypothesized that there would be direct relation between four motivational constructs and intention to pursue math. Math self-concept, math interest, and math utility value were anticipated to be positively related to math intention; math anxiety was expected to be negatively related to math intention. At the same time, I hypothesized statistically significant indirect relations between the four motivational constructs and intention to pursue math via math performance (see *Figure 2.2*). The proposed pathways include associations between motivational constructs and math performance as well as between math performance and math intention. Math self-concept, math interest, and math utility value would each show positive relations to math performance, but math anxiety would show a negative relation. As shown in *Figure 2.2*, current math performance level, in turn, is predicted to show a positive relation to students' intention to pursue math, the educational outcome variable of interest.

In order to examine the moderation effect of cultures in explaining these hypothesized relations above, the model is tested with a comparison between the U.S. and Korea. I assumed that the direction of the proposed paths would be equivalent; however, the relative predictive power of each of the motivational constructs on math performance and intention to pursue math in the future would vary across cultures.

These two nations of U.S. and Korea represent highly distinct cultural settings: Korean education differs from U.S. in terms of the structure of the educational systems implemented as well as the prevailing social and historical norms. Korean culture has been developed under a collectivistic-Confucian Asian cultural tradition that emphasizes modesty of behaviors and hash self-judgement on their ability. Cultural norms emphasize the roles of *societal forces*, including parents, teachers, or peers, so that Korean students' behaviors are likely to be regulated by norms or values of groups (Markus & Kitayama, 1991). In addition, the East Asian cultures, including South Korea, emphasize the value of achievement: hard work and resulting excellence in academic performance are considered the primary and moral obligations of East Asian children (Bempechat & Drago-Severson, 1999). Korean education, like other Asian countries, is characterized as outstanding academic performance on math and science, excessive competition, and high pressure for academic success (Park & Kim, 2014).

Reflecting these different cultural contexts, proposed analyses examined variations in the strength of relations across the *expectancy-value* model. It was hypothesized that Korean students, as compared to U.S. students, would show stronger direct relations between value constructs, especially math interest and math utility value, and intention to pursue math in the future as well as math performance. Because East Asians tend to put more emphasis on task value (i.e., valuing of achievement) rather than beliefs about ability (e.g., Chen & Stevenson, 1995; Wigfield et al., 2004; Zusho et al., 2005), Korean students' task value constructs are more likely to be more strongly associated with math intention and math performance compared to U.S. students. Although not described in the model (*Figure 3.1*), I assumed that there would be mean-level differences in motivational beliefs. Consistent with previous findings (e.g., Eaton & Dembo, 1997; Ho et al., 2000; Zusho et al., 2005), I hypothesized that U.S. students would show higher level of math self-concept, lower level of math interest, math utility value, and math anxiety compared to Korean counterparts.

In order to examine the unique roles of motivational beliefs in explaining relations between the constructs, the study controlled several factors which might affect the prediction of these relations.

Control variables. Gender, grade level, and parental education level were included in this exploration of the hypothesized model. These variables have been considered as important predictors on educational choice intentions.

Gender. A number of studies have showed that gender differences in math are evident in adolescents' motivation as well as choice behaviors (e.g., Meece et al., 1982; Updegraff et al., 1996). In general, boys tend to demonstrate higher value in math, relatively low levels of performance anxiety and higher self-concept than girls. Girls' negative attitudes toward math influence their later career choices and steer them away from mathematics-related fields (Catsambis, 1994). In recent decades, some progress at narrowing the gender gap has been made in math performance (Hyde, Lindberg, Linn, Ellis, & Williams, 2008), ability perceptions for course work (Simpkins & Davis-Kean, 2005), as well as enrollment intentions (Crombie et al., 2005; Stevens, Wang, Olivárez, & Hamman, 2007).

Parental education level. Parental educational level is generally used as a proxy for the family socioeconomic status (SES). In general, highly educated parents are more likely to provide greater learning opportunities to their children and they are available to be engaged in educational interactions at home and at school (Wang & Degol, 2013). Furthermore, there is some evidence that SES influences children's educational aspirations or choice intention, in part, through their impact on the values parents attach to their children's school achievements and college attendance (e.g., Farmer, 1985; Hampden-Thompson & Johnston, 2006).

Grade level[4]. In general, students' motivation in math declines as they advance through school (e.g., Eccles et al., 1998; Jacobs et al., 2002). As children grow up, they become more accurate or realistic in their self-assessments, so that their beliefs about their ability become relatively more negative (Wigfield & Eccles, 2000). Also, as grade level goes up, classroom and school environments change in ways that make evaluation more salient and emphasize competition between students more likely, resulting in decline of some children's achievement beliefs (Wigfield & Eccles, 2000). Thus, along with the negative change in in motivation in math, grade level difference would affect students' intention to pursue in math in the future.

[4] The PISA, the data employed in the dissertation study, is age-based (15-year-olds) so there is a variation in grade within and between countries. A majority of the U.S. and Korean sample is at Grade 10, with 94% of the Korean sample and 71% of the U.S. sample enrolled in Grade 10. However, depending on individual factors such as grade advancement and retention, grade level varies among individuals.

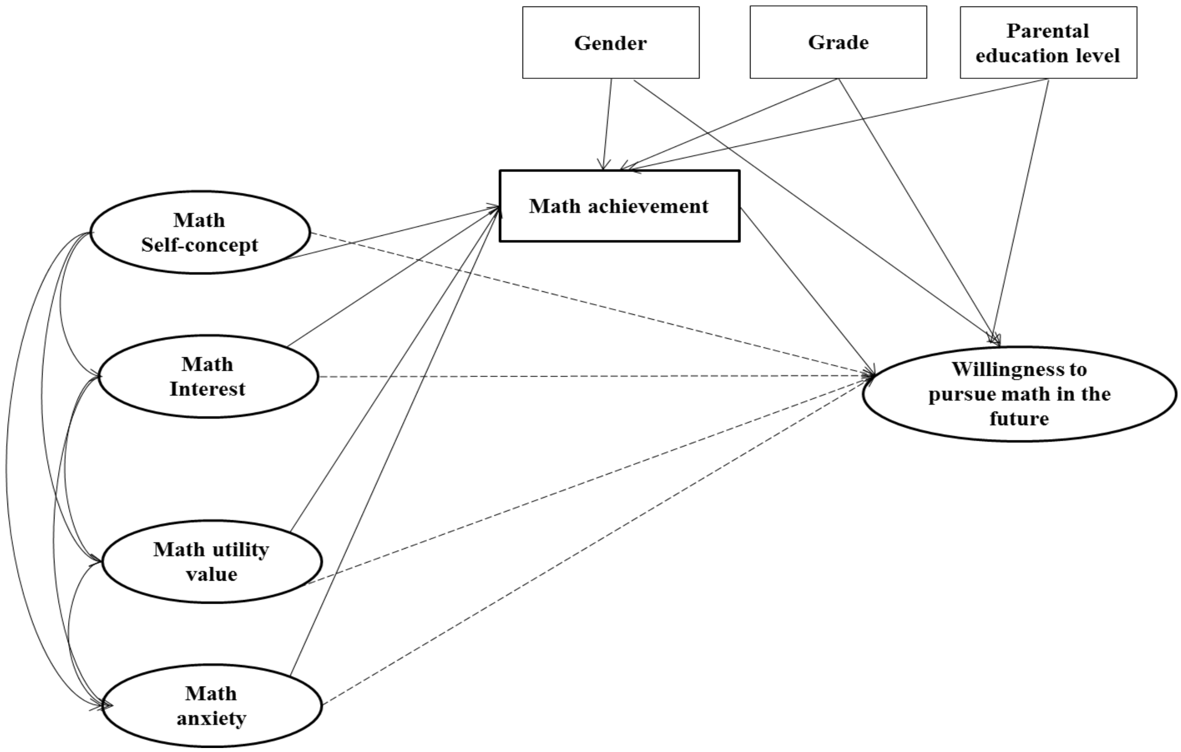

Figure 2.2 A Proposed Conceptual Model

Research Questions and Hypotheses

Here, specific research questions are addressed and hypotheses of each research question are proposed based on the preceding review of the literature.

1. *Does the hypothesized measurement model produce satisfactory goodness-of-fit indices for both the South Korean and U.S sample?* I hypothesized that the proposed measurement model would produce satisfactory goodness-of-fit indices using the following goodness-of-fit indices used for SEM in M*plus* (Muthén & Muthén, 2012). Chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Standardized Root Mean Square Residual, (SRMR), and Root Mean Square Error Approximation Index (RMSEA).

2. *Is each of the motivational beliefs (i.e., math self-concept, math interest, math utility value, and math anxiety) measured invariantly across children across U.S. and Korea?* I

hypothesized that constructs of math self-concept, math interest, math utility value, and math anxiety would be comparable across U.S. and Korea.

3. *If measurement equivalence is established, are there significant differences in mean levels of motivational beliefs variables (i.e., math self-concept, math interest, math utility value, and math anxiety) between U.S. and Korean students?* I hypothesized that there would be significant differences among the mean levels of predictor variables between the U.S. and Korean samples. I hypothesized that U.S. students would show higher levels of math self-concept (Hypothesis 3.1), lower levels of math interest (Hypothesis 3.2), lower levels of math utility value (Hypothesis 3.3), and lower levels of math anxiety (Hypothesis 3.4), compared to Korean counterparts. These predicted relations are consistent with prior research (e.g., Eaton & Dembo, 1997; Ho et al., 2000; Zusho et al., 2005).

4. *Does the hypothesized structural model produce satisfactory goodness-of-fit indices forboth the Korean and U.S. samples?* I hypothesized that that the structural model would fit the data satisfactorily for both the Korean and U.S. samples using the following goodness-of-fit indices discussed above (Muthén & Muthén, 2012).

5. *Are there direct relations of math self-concept, math interest, math utility, and math anxiety to intention to pursue math in the future among both the U.S. and Korean samples?* I hypothesized that there would be direct relations between math self-concept (Hypotheses 5.1), math interest (Hypothesis 5.2), math utility (Hypothesis 5.3), and math anxiety (Hypothesis 5.4) and intention to pursue math in the future among both U.S. and Korean students. These directional relations are consistent with prior research (e.g., Denissen et al., 2007; Durik et al., 2006; Wigfield & Eccles, 2000).

6. *Are there indirect relations of math self-concept, math interest, math utility, and math anxiety to intention to pursue math in the future through current math performance among both U.S. and Korean samples?* I hypothesized that current math performance wouldmediate the relations between math self-concept (Hypothesis 6.1), math interest (Hypothesis 6.2), math utility (Hypothesis 6.3), and math anxiety (Hypothesis 6.4) and intention to pursue math in the future. These relations were proposed based on the preceding review of the literature (e.g., Singh et al., 2002; Spinath et al., 2006).

7. *Are the strengths of these relations described in the structural models equivalent in the two countries?* I hypothesized that the strength of some associations between constructs in the expectancy-value model would vary across samples. Specifically, I hypothesized that there would be stronger direct relations between value constructs (i.e., math interest and math utility value) and intention to pursue math in the futurefor the Korean sample than the U.S. sample. These relations were proposed based on very limited literature (e.g., Chen & Stevenson, 1995; Wigfield et al., 2005).

CHAPTER 3: METHODOLOGY

This chapter provides descriptions of PISA 2012, information about participants and measures used for the present study, and an explanation of how the data were prepared for analysis. Next, a summary of the analytic plans used to investigate each research question are provided. Lastly, hypotheses and analytic strategies are summarized at the end of the chapter.

Overview of the PISA 2012

The current study used data from the PISA 2012, an internationally standardized assessment of student performance in reading, mathematics, science, and financial literacy. The data were developed by the Organization for Economic Cooperation and Development (OECD) and include information on 510,000 students in 65 countries. The goal of the PISA is to "lead to the development of a body of information for monitoring trends in the knowledge and skills of students in various countries as well as in different demographic subgroups of each country" (OECD, 2013a, p.16). The PISA is a cyclical cross-sectional study, with data collections occurring every three years.

The PISA 2012 dataset was chosen for this dissertation because it offers in-depth student information in the scope of mathematics. PISA chooses one of the three core subject areas (i.e., mathematics, science, and reading literacy) in depth as a major subject area for each cycle, and two-thirds of the testing time is devoted to the chosen domain—in 2012, mathematical literacy was the major subject area. Thus, the PISA 2012 met the requirement of measuring motivation as well as achievement in the math domain-specifically. In addition, the benefit of the use of the PISA data is the high quality of data available for analysis. The test items were carefully chosen by expert groups, the sampling was done systematically to ensure generalizability, and test administration was standardized across all sampling locations (Turner & Adams, 2007).

The PISA 2012 Sample

A key characteristic of the PISA sample was the use of an age-based definition for its target population rather than a grade-based definition. OECD (2013a) described the target population as students who were aged 15 years, specifically between 15 years and 3 months and 16 years and 2 months at the time of assessment, and who had completed at least 6 years of formal schooling. The target populations included 15-years-old students in all programs of study, regardless of the type of institution in which they were enrolled, whether they were enrolled full-time or part-time, or whether they attended academic or vocational programs. At this age, students were approaching the end of their compulsory schooling in most participating countries. The PISA 2012 sample was comprised of 510,000 students across 65 countries.

Sampling Design

The PISA 2012 implemented a two-stage stratified sampling design. A minimum of 4,500 students from a minimum of 150 schools was required in each country. The first stage consisted of sampling individual schools in which 15-year-old students were enrolled. Schools were sampled systematically from national lists of all eligible schools. Some of the schools were excluded for approved reasons (e.g., remote location, very small school size, or focus on special education). A minimum of 150 schools were selected in each country. At the second stage, within selected schools, a sample of 35 students was randomly selected in an equal probability sample. Schools were only allowed to exclude students for approved reasons (e.g., students with severe physical disabilities, intellectual disabilities, or insufficient language experience). If fewer than 35 were enrolled in a school, all 15-year-old students were selected. In the PISA 2012 data collection, overall estimated exclusions (including both school and student exclusions) were to be under five percent of the PISA target population in each country (OECD, 2013a).

Data Collection Procedure

For the PISA 2012, countries were required to carry out the survey during a six-week period between March and August 2012. Throughout the survey, all procedures are administered by test administrators employed and trained by National Project Managers within each country (OECD, 2013a).

A paper-and-pencil test for reading, mathematics and science was conducted, lasting a total of two hours for each student. Each student was randomly assigned to one of the 17 different performance test booklets which include a sampling of items. That is, the student answered a portion of questions instead of completing all the possible questions. This testing style, known as an *incomplete booklet design*, was employed because the full assessment is too large for any one student to complete in a reasonable time limit (PISA, 2013a). In an incomplete booklet design, each booklet is composed of four clusters among total of fifteen 30- minute clusters (i.e., seven mathematics clusters, three reading clusters, three science clusters, and two financial literacy clusters). In specific, mathematics, science, and reading clusters are allocated in a rotated design to 13 booklets. The financial literacy clusters in conjunction with mathematics and reading clusters are allocated in a rotated design to four booklets. The average number of items per cluster is 12 items for mathematics, 15 items for reading, 18 items for science, and 20 items for financial literacy. The test consists of a combination of multiple choice and short answer questions. Because each student did not complete a full battery of the test, the test scores were estimated from plausible values. The detailed information about plausible value is provided in the following section (see p. 59-60).

After completing the performance test for two hours, students were asked to answer a 30-minute contextual questionnaire assessing demographic information, psychological factors, teacher-student relation, etc. Because the PISA 2012 contextual questionnaire employed *rotated questionnaire design*, each child was randomly assigned to one of three possible questionnaire booklets (Form A, B, and C). These included a core component (i.e., items were common to all booklets) and a rotated component (i.e., items were different between booklets). A rotated questionnaire design was discussed in more detail (see p. 48-49).

Instrumentation

Math literacy assessment. Math achievement (MATH) was measured by students' performance on math literacy assessment. The PISA intentionally uses the term *mathematics literacy* over mathematics because the term describes a wide range of cognitive competencies in math. PISA aims to examine how well students are prepared to use their knowledge and skills to meet real-life challenges, rather than how well they master knowledge of the curriculum taught in school (OECD, 2013a). This approach differs from other assessment programs (e.g., TIMSS) focusing on the mastery of the school curriculum. During the test, students are expected to demonstrate their mathematics abilities by utilizing information they learned in or out of school and applying it to different real-world situations.

The mathematics literacy items are classified in terms of three interrelated aspects (see p. 38-39, OECD, 2013a): (a) the *processes* that describe what individuals do to connect the context of a problem with the mathematics and thus solve the problem (i.e., formulating situations mathematically; employing mathematical concepts, facts, procedures and reasoning; interpreting, applying and evaluating mathematical outcomes); (b) the *content* that is targeted for use in the assessment items (i.e., change and relationships; space and shape; quantity; uncertainty and data); and (c) the *contexts* in which the assessment items are located (i.e., personal -; occupational -; societal -; scientific context). Approximately 50% of the items are multiple-choice and 20 % are closed or short response types such as requiring a numeric answer to a math problem. For 30% open-ended questions, answers are graded by trained scorers using an international scoring guide.

Student context questionnaire. PISA 2012 student context questionnaire collected information about important antecedents and processes of student learning at the individual, school, and system level. In the collection of PISA 2012 data, a *planned rotated design* of the student context questionnaire was used for the first time in order to increase the content coverage of topics of interest without increasing the response time for participants to more than 30 minutes. Each participant randomly received one of three possible questionnaire booklets (Form A, B, and C).

Each booklet contains two parts, namely the *common* and the *rotated* part. The common part contains those questions which are answered by all students, including grade, gender, parental education and occupation, educational resources (e.g., desk, computer for school work), cultural possessions (e.g., books of poetry, works of art), immigration status, heritage language (OECD, 2013a). The rotated part contains questions about students' attitudinal and noncognitive constructs that are allocated into the three question sets. Question set 1 contained items covering attitudes towards mathematics and the problem-solving strategies. Question set 2 included items on climate in the mathematics classroom, attitudes towards school, math self-concept and math anxiety. Question set 3 consisted of items measuring *Opportunity to Learn* (e.g., learning time and experience with various kinds of mathematical tasks) and learning strategies (OECD, 2013a). Each booklet contains two of the three question sets to allow joint analyses of these constructs (see Table 3.1).

The PISA 2012 technical manual (OECD, 2013b) reported the result of extensive analyses that had been undertaken to examine the potential impact of the use of the rotated design on the continuity of the results. For example, Adams, Lietz, and Berezner (2013) simulated the outcomes of the use of different rotated context questionnaire designs using rescaled PISA 2006 data. They reported that regardless of whether they scaled the data using rotated context questionnaires or nonrotated questionnaires, the results revealed very similar trends when means, standard deviations, percentiles of context variables were estimated.

Table 3.1

Final design of rotated student context questionnaires in PISA 2012

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

Cross-National Validation

Test material selection and translation processes are top priorities of the OECD due to its use across a diverse range of educational systems and cultures. To provide reliable and comparable information across cultures, PISA measures were developed using a complex procedure. A brief summary of the cross-national validation process used in PISA is introduced here.

Test development. One of the strengths of the PISA datasets is its ability to provide cultural and linguistic equivalence in the assessment materials. The objective is accomplished by including each participating country in the item development and revision processes (OECD, 2013a). The PISA 2012 assessment tools were developed by international experts and PISA consortium test developers. All participating nations were permitted to submit items for consideration and each was considered by a consortium test development team. Representatives from each education system (i.e., PISA Governing Board) and PISA subject-matter expert groups reviewed these items for relevance to PISA's goals and for possible bias. These groups were invited to comment on the difficulty level, cultural appropriateness, and curricular and non-curricular relevance of test items. After initial development, items judged "worthy of inclusion" were translated into French and English and then a subsequent lengthy selection process was undertaken. This process included two phases of scrutiny by local teams, sample testing with small groups of students, and pilot testing with larger student populations (OECD, 2013b).

Translation and verification process. Once items were selected, the French and English versions were sent to all participating nations. Each participating nation was responsible for translating all test items into their national languages. Because translation errors often result in items functioning poorly on international tests (McQueen & Mendelovits, 2003), PISA implemented strict procedures for translation and verification of all survey instrumentation. These verification procedures included: (a) employing a double translation design (i.e. two independent translations by two translators and reconciliation by a third person); (b) developing detailed translation guidelines for the test material and for revisions; (c) training key staff on each national team in translation procedures; and (d) appointing and training professional translators proficient in English and French with native command of each target language in order to verify the national versions against the source versions (OECD, 2013b).

Overview of Current Study

Sample for the Current Study

Sample selection. According to the PISA 2012 technical report (OECD, 2013b), of Korea's target population (672,101 15-year-old students who enrolled in Grade 7 or above), 5,033 students from 165 schools participated in the collection of the PISA 2012. In the United States, among the 4,074,457 target population (15-year-old students who enrolled in Grade 7 or above), 4,978 students from 162 schools participated in the data collection. However, to be eligible for the present analysis, the sample was restricted to observations where complete information is available on all variables (i.e., math self-concept, math interest, math utility value, math anxiety, and intention to pursue math). Therefore, only one third of the total sample who was assigned to Form B were included in the final sample (Korea = 1,691 cases, U.S. = 1,665 cases, see Table 3.2). For those questions that were not administered to a student, missing data were recorded with a special code (i.e., 7 = Not Applicable) in the original dataset. Lastly, due to some unexpected reasons including when a poorly printed item was presented to the student (OECD, 2013b), some students were was unable to provide a response through no fault of their own. These cases were excluded in the final sample (Korea = 2 cases, USA= 13 cases). Thus, the final analytic sample included 1,689 Korean sample and 1,652 U.S. sample.

Table 3.2

Numbers and Percentage of Students by the Type of Forms

		Number of students	Percentage
Korea	Form A	1,669	33.2
(*N* = 5,033)	Form B	1,691	33.6
	Form C	1,673	33.2
U.S.	Form A	1,654	33.2
(*N* = 4,978)	Form B	1,665	33.4
	Form C	1,659	33.3

Description of the final sample. Table 3.3 and 3.4 present the unadjusted percentage distribution of demographic characteristics of the analytic sample and the comparable PISA 2012 full sample of Korea and U.S. For every characteristic, the analytic sample numbers and percentages were highly similar or identical to the PISA 2012 full sample as well as the excluded samples.

The final Korean sample included 800 (47.5%) female students and 891 (52.6%) male students. With regard to grade level, most of the Korean sample was at Grade 10 (94.0%), with 5.9% at Grade 9, and 0.1% at Grade 11. And 51.9% of Korean sample reported the total number of years of parental education to be 16 years. 31.9% of students reported 12 years, 5.2% of students reported 14 years, and 2.9% of students reported 9 years. For the U.S. sample, 795 (48.1%) female students and 857 (51.9%) male students were included in the analysis. 73.1% of participants were at Grade 10, 16.0% were at Grade 11, and 10.5% were at Grade 9. There were small percentages of students who were at Grade 8 (0.2%) and Grade 12 (0.2%) in U.S. sample. Regarding the total number of years of parental education, 44.4% of students reported 16 years, 32.6% of students reported 12 years, and 14.5% of students reported 14 years.

Table 3.3

Distribution of PISA Full Sample, Final Analytic Sample, and Excluded Sub-Samples by Adolescents' Characteristics: Korean Sample

	PISA Full Sample (*N* = 5,033)	Final Analytic Sample (*N* = 1,689)	Excluded Sub-Samples	
			Form A (*N* = 1,669)	Form C (*N* = 1,673)
Gender				
Female	2,342 (46.5%)	800 (47.5%)	776	766
Male	2,691 (53.5%)	889 (52.6%)	893	907
Grade				
9	295 (5.9%)	100 (5.9%)	101	94
10	4728 (93.9%)	1588 (94.0%)	1565	1573
11	10 (.2%)	1 (.1%)	3	6
Years of Parental Education				
3	11 (.2%)	5 (.3%)	3	3
6	28 (.6%)	11(.7%)	7	10
9	120 (2.4%)	49 (2.9%)	36	35
12	1,993 (40.0%)	653 (31.9%)	665	675
14	326 (6.5%)	87 (5.2%)	118	121
16	2,505 (50.3%)	867 (51.9%)	830	808

Table 3.4

Distribution of PISA Full Sample, Final Analytic Sample, and Excluded Sub-Samples by Adolescents' Characteristics: U.S. Sample

	PISA Full Sample (N = 4,978)	Final Analytic Sample (N = 1,652)	Excluded Sub-Samples	
			Form A (N = 1,669)	Form C (N =1,673)
Gender				
Female	2,453 (49.3%)	795 (48.1%)	852	804
Male	2,525 (50.7%)	857 (51.9%)	802	855
Grade				
8	6 (.1%)	3 (.2%)	2	1
9	538 (10.8%)	174 (10.5%)	188	174
10	3633 (73.0%)	1207 (73.1%)	1216	1200
11	794 (16.0%)	265 (16.0%)	247	281
12	7 (.1%)	3 (.2%)	1	3
Years of Parental Education				
3	43 (.9%)	15 (.9%)	17	11
6	117 (2.4%)	36 (2.2%)	36	45
9	262 (5.4%)	86 (5.3%)	99	77
12	1,566 (32.2%)	528 (32.6%)	500	538
14	699 (14.4%)	235(14.5%)	229	235
16	2,182 (44.8%)	720 (44.4%)	740	722

Variables Used in the Current Study

The full set of variables employed in this analysis includes (a) four independent variables, (b) one outcome variable, (c) one mediator variable, and (d) three control variables. Except math performance level as a mediating variable that was attained from performance test, other variables were measured in the student's contextual questionnaire. The following section provides a more detailed description of variables for the proposed analysis as well as the scale reliability information (i.e., Cronbach's alpha for each national sample). I calculated reliability estimates for each construct using samples included in the analysis.

Independent variables. Four independent variables were included in the analysis.

Math self-concept. Math self-concept (SCMAT) refers to students' beliefs in their own mathematics ability. The PISA 2012 participants responded to five math self-concept items that were presented with a four-point Likert-type response (strongly agree = 1, agree = 2, disagree = 3, and strongly disagree = 4): (a) I have always believed that mathematics is one of my best subjects (ST42Q07); (b) I learn mathematics quickly (ST42Q06); (c) In my mathematics class, I understand even the most difficult work (ST42Q09); (d) I get good grades in mathematics (ST42Q04); and (e) I am just not good at mathematics (ST42Q02). The Cronbach's alpha is .88 for Korean and .90 for U.S. students.

***Math interest value*.** Math interest value refers to students' attraction to, liking of, and enjoyment of math. The PISA 2012 labels the variable as intrinsic motivation (INTMAT). However, the definition of the variable was initially constructed based on Eccles et al.'s expectancy-value theory (OECD, 2013a), as well, items measuring intrinsic motivation in PISA (Table 3.5) closely resemble interest value items from scales commonly used in primary expectancy-value research (Wigfield & Eccles, 2000). Thus, these four items are used in this study as math interest value measures. The items were presented with a four-point Likert-type response (strongly agree = 1, agree = 2, disagree = 3, and strongly disagree = 4). The Cronbach's alpha is .90 for Korean and .92 for U.S. students.

Table 3.5

Intrinsic Motivation Items from the PISA 2012 Compared to Items from the study of Wigfield and Eccles (2000)

PISA 2012	Wigfield and Eccles (2000)
I enjoy reading about mathematics (ST29Q01)	In general, I find working on math assignments (very boring- very interesting [fun])
I look forward to my mathematics lesson (ST29Q03)	How much do you like doing math? (not at all - very much)
I do mathematics because I enjoy it (ST29Q04)	
I am interested in the things I learn in mathematics (ST29Q06)	

Math utility value. Math utility value refers to the desire to learn mathematics because students consider it useful for the attainment of their goals. The PISA labels this variable as an *instrumental motivation* (INSTMOT). Given the close match between these items and standard utility value items used in primary research (Table 3.6), these four items were used in this study as *math utility value* measures. The Cronbach's alpha is .91 for Korean and .90 for U.S. students.

Table 3.6

Instrumental Motivation Items from the PISA 2012 Compared to Items from the study of Wigfield and Eccles (2000)

PISA 2012	Wigfield and Eccles (2000)
Making an effort in mathematics is worth it because it will help me in the work that I want to do later on (ST29Q02)	Some things that you learn in school help you do things better outside of class, that is, they are useful. For example, learning about plants might help you grow a garden. In general, how useful is what you learn in math? (not at all useful - very useful)
Learning mathematics is worthwhile for me because it will improve my career prospects (ST29Q05)	Compared to most of your other activities, how useful is what you learn in math? (not at all useful - very useful)
Mathematics is an important subject for me because I need it for what I want to study later on (ST29Q07)	
I will learn many things in mathematics that will help me get a job (ST29Q08)	

Math Anxiety. Five math anxiety items (ANXMAT) were used in the study: (a) I get very nervous doing mathematics problems (ST42Q05); (b) I get very tense when I have to do mathematics homework (ST42Q03); (c) I often worry that it will be difficult for me in mathematics classes (ST42Q01); (d) I feel helpless when doing a mathematics problem (ST42Q08); and (e) I worry that I will get poor grades in mathematics (ST42Q10). The Cronbach's alpha is .73 for Korean and .88 for U.S. students.

Outcome variable. In the current study, *intention to pursue math in the future* (called from now as *math intention*) refers to students' intentions to focus on mathematics in their future studies and careers, rather than pursuing other academic subjects such as English (Korean). In the PISA 2012 dataset, *mathematics intentions* (MATINTFC) was measured by asking students to choose the statement that best described them from each pair of the statements described in the Table 3.7. Respondents were required to choose either mathematics-related behaviors (coded as 1) or either science - or the test language - related behaviors (coded as 2). This *Forced - Choice* item format is one of the new item types initially employed in PISA 2012. Instead of evaluating each statement in relation to a rating scale (i.e., Likert-type items), students have to choose between statements according to the extent these statements describe their preferences or behavior (Brown & Maydeu-Olivares, 2012). In the PISA 2012, it forced students to make *comparative judgements*, deciding between only two choices (i.e., mathematics versus English/Korean). The forced - choice item format has advantages over a Likert-type response format in that it reduces some common response biases, such as social desirability (OECD, 2013a).

For the current study, instead of using the whole set of items measuring math intention, I determined to employ only two items that compare the extent of intentions to pursue between mathematics and English (Korean): (a) I intend to take additional mathematics courses after school finishes vs. I intend to take additional English (Korean for Korean sample) courses after school finishes (ST48Q01), and (c) I am willing to study harder in my mathematics classes than is required vs. I am willing to study harder in my English (Korean) classes than is required (ST48Q03). A number of motivation studies have argued that the subject domains of math and science are highly correlated. For example, if students have both high math interest and math utility value, they are likely to have a particularly high task value in science (Chow & Salmela-Aro, 2011). Science requires math; math self-ability beliefs are related to college students' choice of science-based academic majors (Lent, Lopez, & Bieschke, 1991) or technical/scientific vocational interests (Lapan, Boggs, & Morrill, 1989). Based on these findings, theoretically, it may be assumed that intentions to pursue math in the future should be highly correlated with intentions to pursue science in the future. Thus, in order to increase the robustness of the measurement scale, I extracted three items that compare the extent of intentions to pursue between mathematics and science. The information about how to create a dependent variable using two selected items was provided at the next section (see p. 63-64).

Table 3.7

Math Intention Items from the PISA 2012

PISA 2012			Current Study
choose the statement that best described them from each pair of the following statements			
ST48Q01	a)	I intend to take additional mathematics courses after school finishes	√
	b)	I intend to take additional English (Korean) courses after school finishes	
ST48Q02	a)	I plan on majoring in a subject in a college that requires mathematics skills	
	b)	I plan on majoring in a subject in a college that requires science skills	
ST48Q03	a)	I am willing to study harder in my mathematics classes than is required	√
	b)	I am willing to study harder in my English (Korean) classes than is required	
ST48Q04	a)	I plan on taking as many mathematics classes as I can during my education	
	b)	I plan on taking as many science classes as I can during my education	
ST48Q05	a)	I am planning on pursuing a career that involves a lot of mathematics	
	b)	I am planning on pursuing a career that involves a lot of science	

Note: √ indicates whether the item was included in the current study

Mediating variable. Mathematics performance was hypothesized to mediate relations between motivation beliefs and math intention. The current study employed five plausible scores of math literacy as indicators of math performance (PV1MATH - PV5MATH). The PISA 2012 assessed math literacy using an *incomplete booklet design*. This design requires that individual students respond to a relatively small number of items from the overall battery of assessment items in order to reduce time demands on each student. Thus, because each student responds to only a selection of possible items, a test score distribution (i.e., plausible value) is estimated for each individual using missing-data imputation techniques (Graham, 2009) and Item Response Theory (Foy, Galia, & Li, 2007). In other words, each plausible value assigned to an individual student is not the actual score of a student; there is a randomly selected score from the estimated distribution of scores that a student might have obtained had he or she completed the full test (OECD, 2013b).

Because analyses that involve math literacy variables are recommended to be conducted with the five plausible values (OECD, 2013b), in the current study, any estimation procedure involves the calculation of the required statistic five times, one for each of plausible values. These plausible scores were standardized scores with an average score of 500 and a standard deviation of 100, which means that two-thirds of students across OECD countries scored between 400 and 600 points. Table 3.8 provides some descriptive information on math plausible values for the Korean and U.S. sample.

Table 3.8

Descriptive Information on Math Plausible Values

	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
Korea						
PV1	183.99	825.83	557.00	97.60	-.16	-.11
PV2	226.06	902.95	554.61	96.19	-.14	-.13
PV3	170.83	818.05	553.52	97.40	-.12	-.14
PV4	191.00	836.82	554.96	96.94	-.07	-.11
PV5	240.07	866.59	555.58	96.19	-.11	-.16
U.S.						
PV1	174.02	761.97	484.70	88.12	.13	-.13
PV2	230.88	759.54	485.02	88.79	.16	-.25
PV3	237.90	783.70	485.24	88.94	.18	-.24
PV4	227.85	775.91	485.76	88.43	.16	-.19
PV5	188.90	778.63	486.15	88.68	.17	-.12

Control variables. Three control variables were included in the analysis. Controlling for pre-existing within-country student differences allows for a more precise analysis of the contribution of motivational beliefs on math performance and math intention.

Gender. The variable for gender is categorical with two response options (male = 1; female = 2). Dummy variables were created for analyses with female as the reference category.

Grade. Given that the PISA samples are age - based, grade level differed across participants even they were all 15-years old. In order to improve the efficiency of interpretation, PISA provides the *relative grade* information (GRADE), which identifies how far students are from the modal grade, referring to the grade in which the greatest number of students of the age is enrolled (OECD, 2013a). Grade 10 serves as the modal grade in both the US and Korean data sets.

Parental education level. The PISA provides information of highest educational level of parents corresponding to the higher level of International Standard Classification of Education (ISCED) of either parent. According to ISCED, U.S. and Korean education level is scaled from 0 to 6 (see Table 3.9). The current study utilized the information of the total number of years of parental schooling (PARED).

Table 3.9

ISCED Educational Classification Scheme

Level	Description	Years of schooling
0	Kindergarten and below, did not attend school	3
1	Primary education	6
2	Lower secondary	9
3B/3C	Vocational/pre-vocational upper secondary	12
3A/4	Upper secondary and/or non-tertiary post-secondary	12
5B	Vocational tertiary	14
5A/6	Theoretically oriented tertiary and post- graduate	16

Preparation of Data for Analysis

This section describes the process for the preparation of data for analysis. First, I present information about the construction of the dataset. Next, I describe statistical issues including data screening, estimation method, and missing data. Lastly, I describe the sampling weights and design weights applied in this study

Construction of Analysis Dataset

I extracted publicly available data from OECD official website (http://pisa2012.acer.edu.au) using SPSS Statistics Version 21 software package. From the whole dataset, I extracted only Korean and U.S sample data first and then among these data, I extracted only the samples who were assigned to Form B. Then, I recoded some items and constructed some items. Then, files were imported into M*plus* Version 7 for subsequent analyses.

Recoded measures. I recoded response to eighteen motivational belief items (i.e., math self - concept, math interest, math utility value, and math anxiety) so that higher scores reflect stronger evidence of the underlying construct (strongly disagree = 1, disagree = 2, agree = 3, and strongly agree = 4). In addition, I also recoded responses to the items that measured math intention. In the original data, respondents who chose math-related behaviors were allocated as 1 and those who chose test language-related behaviors were allocated as 2. For analytical purposes, I recoded these responses into binary numbers that indicated the absence (coded as 0) or presence (coded as 1) of respondents' intention to pursue math rather to pursue other subjects.

Creation of a dependent variable. I created the latent dependent variable of math intention for this dissertation study. As discussed earlier (see p. 59-60), the PISA dataset originally provides the composite score of the mathematics intentions (MATINTFC), which was calculated as a ratio of a sum of all five questions over maximum score of valid responses using Item Response Theory (IRT) scale as well as a raw score of each of five questions (OECD, 2013b). However, due to the concern about theoretically strong associations between math and science (i.e., science requires mathematics essentially), I decided to omit three items that compare the extent of intentions to pursue math versus science and employ only two selected items that compare the extent of intentions to pursue mathematics versus language (ST48Q01 and ST48Q03) in the current study.

To confirm if the relatively stronger correlations between omitted items that compare intentions to pursue mathematics versus science (ST48Q02, ST48Q04, and ST48Q05) exist, I conducted a correlation analysis. The result showed that there were strong, positive correlations between these items (mathematics versus science) ranged from .60 to .80. In contrast, the correlations between these items and items that compare intentions to pursue mathematics and language (ST48Q01 and ST48Q03) were ranged from .17 to .22.

Based on theoretical perspectives and statistical evidence, I created a latent variable for students' intention to pursue math in the future using these two items: (a) I intend to take additional mathematics courses after school finishes vs. I intend to take additional English (Korean for Korean sample) courses after school finishes (ST48Q01) and (b) I am willing to study harder in my mathematics classes than is required vs. I am willing to study harder in my English (Korean) classes than is required (ST48Q03). A response is coded as 1 when a student chooses mathematics over the test language (coded as 0). Thus, each item is considered as an observed *categorical variable* with dichotomous response categories.

Categorical data. In addition to math intention items which have dichotomous response options, eighteen motivation items are ordered-categorical in nature: the intervals between each Likert response are not statistically equivalent (Carifio & Perla, 2008). In general, Likert-type indicators are often treated as continuous when they follow a normal distribution and have at least five but preferably seven response categories (Lubke & Muthén, 2004). However, the current data have only four response categories and did not sufficiently meet assumptions of normality. Thus, I decided to define the data as categorical and employed an appropriate estimation method for categorical data in the analysis (i.e., WLSMV).

Analytic Strategies

Statistical programs. Data were analyzed using SPSS version 22.0 and M*plus* version 7. I used SPSS to generate available dataset and conduct descriptive statistics. And I used M*plus* to test for testing measurement models and structural models hypothesized in this study. M*plus* is an appropriate statistical program for the current study for the following reasons: (a) it analyzes a combination of categorical and continuously scored variables, (b) it handles issues related to non-normal distributions or nested data easily, and (c) it utilizes a full information maximum likelihood technique (FIML) to handle missing data (Muthén & Muthén, 2012).

Applying weights. The PISA 2012 dataset was not collected through simple - random sampling. Rather, the data were collected with a two-stage sampling design. First, schools were sampled and then students were sampled in the participating schools. Most of the statistical packages assume the data were collected by simple-random sampling, and as a result, analyzing the PISA data with such software systematically underestimates the standard errors which lead to reporting non significant results as significant (OECD, 2013b). Thus, I applied two processes in the current study: applying *survey weights* to provide more accurate population estimates and applying *replicate weights* to obtain accurate standard errors.

***Applying survey weights*.** I used a survey weight to adjust the sample to be nationally representative of target population. In essence, survey weights are inversely proportional to the probability of selection. Samples with a higher probability of selection have smaller survey weight values.The PISA data file provides the weight variable, which is referred to the *final student weight* (W_FSTUWT). This weight can account not only for the probabilities of selection of individual schools and students, but also for school or student nonresponses, and errors in estimating a size of the school or the number of 15-year-olds enrolled at the time of sampling (OECD, 2013a). The use of the *final student weight* (W_FSTUWT) ensures that the sample is properly and proportionally represented in the computation of population estimates.

***Applying replicate weights*.** As discussed before, the PISA 2012 data collection process followed a two-stage sampling technique. Due to the impact of clustering, there may exist homogeneity within the clusters (i.e., schools). That is, students attending a same school are more likely to have common characteristics (e.g., teachers, curricula, etc.) than students attending different schools. For example, a simple random sample of 5,000 students is therefore likely to cover the diversity of the population better than a sample of 100 schools with 50 students observed within each school (OECD, 2013a). And it would lead to underestimation of the true variability in the population (i.e., underestimated variance and standard errors). The PISA technical manual (OECD, 2013b) recommends the use of replication sampling variance estimation technique, which is called Fay variant of the Balanced Repeated Replication (BRR), in order to produce correct standard error estimates. PISA provides 80 different sampling weights (W_FSTR1 to W_FSTR80). Using these weights, estimations are repeated 80 times, providing 80 different estimates of each parameter, enabling the construction of a sampling distribution for each estimator.

In the recent version of M*plus*, the replication methods including BRR are available for estimating sampling variances with complex data. However, when replicate weights were used for computation in this study analysis, the output did not provide statistics of chi-square because "one problem with the application of replication methods in SEM is that the chi- square statistic for each of the replications does not account for the sampling design" (Stapleton, 2008, p.196).

Alternatively, in order to account for the nested nature of the dataset, both the sample stratification variable (WVARSTRR) and the primary sampling unit (SCHOOLID) were specified in the current study. M*plus*' STRATIFICATION and CLUSTER options were used to adjust for any non-independence of observations. When these sampling variables are specified, the standard errors are adjusted to account for the unequal probability of selection (Asparouhov, 2005).

Plausible values. As discussed earlier, math performance was measured using plausible value technique. Plausible values are not the actual scores of a student; there is a distribution of scores that a student might have obtained had he or she completed the full test (OECD, 2013b). Thus, all analyses that involve math performance are recommended to use the five plausible values in order to increase reliability of the resulting data (OECD, 2013b). That is, any estimation procedure involves the calculation of the required statistic five times, one for each of plausible values. Thus, in this study, the hypothesized model was tested five times using five different plausible values of math performance.

Data Screening

All variables were screened for statistical assumption violations, as well as for missing values and outliers.

Normality. Initially, data were screened for violations of normality. All items were skewed to various degrees, skewness statistics ranged from -.69 to .62. Values for kurtosis ranged from -2.00 to .32. With regard to univariate normality, Kline (2011) states that the absolute value of skewness greater than 3 and kurtosis value greater than 10 may indicate a problem. None of the items in the current study exhibited extreme skew or kurtosis[5].

Missing Data. Missing values were screened using subpopulations of the Korean (*n* = 1,689) and U.S. samples (*n* = 1,652). The 18 observed indicators in the measurement model had percentages of missing values ranging from 0.2% to 5.75% (see Table 3.10). Although there is no consensus on the percentage of missing data that becomes problematic (Schlomer, Bauman, & Card, 2010), less than 5% of data that are missing is not likely to bias statistical analyses

[5] The formal normality tests including Shapiro-Wilk test and Kolmogorov-Smirnov test as well as absolute z-scores (obtained by dividing the skew values or excess kurtosis by their standard errors) were not utilized in the study because they are unreliable for large sample (Tabachnick & Fidell, 2013).

(Schafer, 1999). Next, Little's MCAR test was conducted using the missing value analysis (MVA) option of SPSS (IBM, 2010) and the result was significant at $p < .05$ level, indicating that the data do not meet the assumption of missing completely at random (MCAR). Thus, listwise deletion may yield biased estimates. Rather, in the current study, missing data were handled using full information maximum likelihood (FIML) procedures in M*plus*. This technique does not replace missing values but estimates parameters based on the available complete data as well as the implied values of the missing data given the observed data (Schlomer et al., 2010). FIML has two advantages over imputation approaches: (a) the imputation and the analysis are simultaneously conducted and (b) FIML generates accurate standard errors by retaining the sample size (Schlomer et al., 2010).

Table 3.10

Summary of Missing Cases

	Korea		USA	
Variable	Count	Percent	Count	Percent
Gender	0	0	0	0
Grade	0	0	0	0
Parental education level	17	1.0	32	1.9
MSC: Not good at math (R)	4	0.2	40	2.4
MSC: Get good grades in math	4	0.2	40	2.4
MSC: Learn quickly	6	0.4	47	2.8
MSC: One of best subjects	6	0.4	42	2.5
MSC: Understand difficult work	6	0.4	41	2.5
MIV: Enjoy reading about math	5	0.3	24	1.5
MIV: Look forward to lessons	5	0.3	25	1.5
MIV: Enjoy math	5	0.3	30	1.8
MIV: Interested in the things I learn	5	0.3	29	1.8
MUV: Worthwhile for work	4	0.2	28	1.7
MUV: Worthwhile for career chances	5	0.3	29	1.8
MUV: Important for future study	4	0.2	29	1.8
MUV: Helps to get a job	5	0.3	34	2.1
MA: Worry that it will be difficult	3	0.2	34	2.1
MA: Get very tense	4	0.2	45	2.7
MA: Get very nervous	5	0.3	41	2.5
MA: Feel helpless	5	0.3	46	2.8
MA: Worry about getting poor grades	5	0.3	37	2.2
MI: Choose math course after school	17	1.0	94	5.7
MI: Study harder in math	16	0.9	91	5.5
Math performance (PV1MATH - PV5MATH)	0	0	0	0

Note. MSC = math self-concept; MIV= math interest value; MUV = math utility value; MA = math anxiety; MI = intention to pursue math in the future

Multicollinearity. To assess collinearity in each indicator in the proposed model, Spearman's correlation was calculated. There were no pairs of indicators that displayed overly large bivariate correlations that reached 0.85 or higher (Kline, 2011). An absence of highly correlated pairs within the matrix indicates an unlikely chance that a multiple correlation, or multicollinearity, exists within the indicators.

Analysis Procedures

Overview of Data Analytic Strategy

Initially, I conducted descriptive analyses to describe the characteristics of the sample. Latent variables were assessed through univariate statistics, including mean, median, standard deviations, skewness, and kurtosis.With regard to analysis related to research questions, the analyses of data consist of five steps: (1) testing the factor structure of the measurement model (Research question 1), (2) testing the equivalence of the measurement model (Research question 2), (3) examining mean differences of constructs (Research question 3), (4) testing the model fit of the structural model (Research question 4) and testing hypothesized direct and indirect relations depicted in the conceptual model (Research question 5 and 6), and (5) testing the equivalence of the structural model (Research question 7).

The first part of the analysis is related to testing the measurement model. The measurement model is the part which relates measured variables to latent variables, thus, it includes math self-concept, math interest, math utility value, math anxiety, and math intention. In order to test the measurement model of the study, I employed a mean and covariance structure (MACS) approach. The second part of the analysis is related to testing the structural model, the part that relates latent variables to one another. In order to test the structural model, I examined hypothesized paths in the proposed model described in *Figure 3.1*. In the structural model, there are four exogenous (i.e., independent) factors (Math Self-Concept, Math Interest, Math Utility Value, Math Anxiety) and two endogenous (i.e., dependent) factors (Math Performance and Intention to Pursue Math in the Future). I proposed a partial mediation model in which both direct and indirect effects of motivational beliefs on intention to pursue math in the future are presented after controlling the effect of gender, grade, and parental education level. The paths between exogenous variables and endogenous variables were hypothesized as follows: (a) the four types of motivational beliefs have direct effects on both math performance and intention to pursue math in the future; (b) the four motivational beliefs directly relate to math performance as well as have indirect effects on intention to pursue math in the future through math performance after controlling. I estimated the hypothesized paths between exogenous and endogenous as *path coefficients*. A multiple group SEM analysis was employed to test the structural part of the model.

I conducted the above analysis using M*plus* Version 7 with the WLSMV estimator (Muthén & Muthén, 2012). In remaining sections, I discuss the analysis technique (i.e., mean and covariance structure analysis) and then introduce the specific procedures of the analysis.

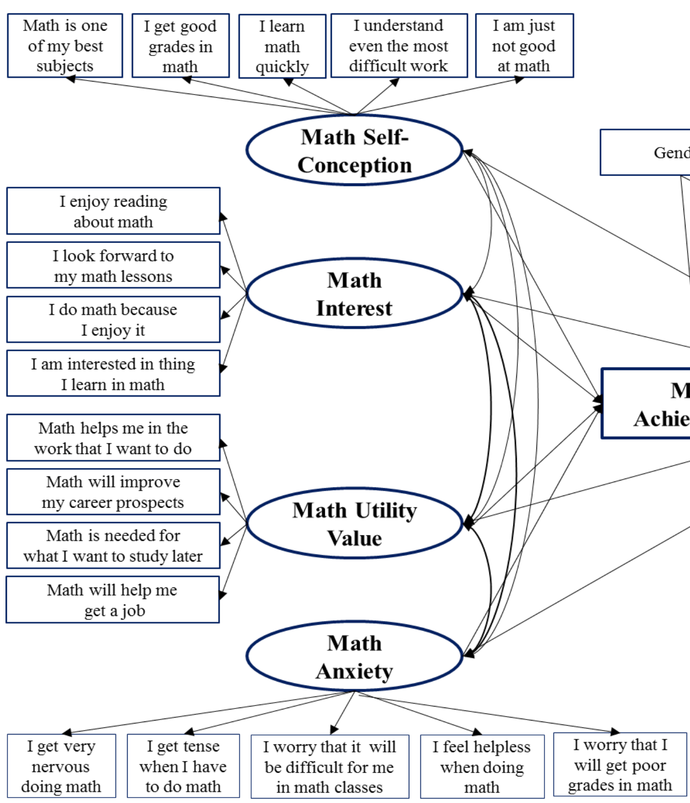

Figure 3.1. The Proposed Structural Model

Mean and Covariance Structure (MACS) Analysis

I employed the mean and covariance structure analysis (MACS) in the current study. MACS is a variation on traditional structural equation modeling (SEM), which directly tests the measurement equivalence of constructs by examining both latent means and covariance structures of the data (Little, 1997). In other words, the critical extension is that MACS analysis utilizes the mean-level information in addition to the variance-covariance information.

MACS analysis has several statistical advantages (Little, 2000). First, it includes basic advantages of SEM such as correcting for measurement error and explicitly testing the validity of relations among the measured variables. Second, it directly tests and validates the measurement equivalence of the constructs and also detects between-group differences in means, variances, and intercorrelations of latent constructs. Third, MACS also allows researchers to test hypotheses related to group differences in the relations between constructs. This approach also accounts to a large extent for the extreme response style and acquiescent response style (i.e., a tendency to agree or disagree with all items in a survey irrespective of their content) that have been found to sometimes occur in cross-cultural measurement research (Little, 1997, 2000).

Estimation. I employed the weighted least squares multivariate estimation (WLSMV) for estimating the fit of the hypothesized measurement and structural models. Muthén, Muthén, and Asparouhov (2015) noted that the WLSMV is the most advantageous estimator with ordinal and non-normally distributed data. When categorical variables are treated as continuous and analyzed with general maximum likelihood (ML) procedure, biased parameter and standard error estimates are likely to be generated so that model-data fit is often underestimated (Kline, 2011).

The WLSMV estimator handles ordinal data by creating a special correlation matrix that takes into account the measurement level of the variables. The correlation matrix assumes that:

(a) a unidimensional latent variable (e.g., math anxiety) underlies the item responses, (b) the latent variable has a continuous distribution which is not specified explicitly, and (c) there are thresholds on this distribution at which a respondent chooses one ordinal response category rather than another (Flora & Curran, 2004). Thus, respondents “locate themselves on the latent continuum by selecting a response category that best expresses their position on that continuum.”(Hernández & González-Romá, 2003, p. 323) Each ordinal variable generally have multiple thresholds, specifically, one fewer thresholds than the number of response categories.

Step 1: Measurement Model Specification

First, I conducted confirmatory factor analyses (CFAs) separately with each group to determine whether the underlying factor structure of the data was consistent with the factor structure hypothesized by PISA developers. In other words, I tested the pattern of indicators-to-construct relations, which include factor loadings and intercepts (i.e., the measurement model). Here, overall model fit, parameter estimates, and modification indices were examined and model respecification was undertaken if warranted. In cases of poorly fitting models, I examined modification indices, explained variance, and residual correlations in order to find possible areas of model misspecification. I changed one parameter at a time and then tested and evaluated a respecified model before considering further modifications (Byrne, 2012). Model respecifications were undertaken only when there was strong theoretical rationale for why they work (Byrne, 2012).

Goodness-of-fit indices. I used several model fit indices were used to determine the suitability of the models: the chi-square statistic (χ^2), Tucker-Lewis Index (TLI), Bentler and Bonetts’ Comparative Fit Index (CFI), and the Root Mean Squared Residual Error Approximation (RMSEA). The χ^2 statistic represents a measure of overall model fit and a non-significant χ^2 is indicative of overall good model fit (Bowen & Guo, 2012). However, due to the sensitivity of the χ^2 statistic to large sample sizes (Bowen & Guo, 2012), I used additional fit indices. Consistent with the most current guidelines, TLI and CFI values between .95 and 1.0 and RMSEA values less than .6 indicate that the model provides a good fit to the data (Hu & Bentler, 1999). RMSEA values between .06 and .08 are considered indicative of reasonable model fit (Browne & Cudeck, 1992). The 90% confidence interval (CI) of the RMSEA value is also considered to account for imprecision in the RMSEA point estimate; an upper bound CI value of .08 or less is considered indicative of good fit.

Modification. Modification indices (MIs) are typically provided by M*plus* in order to serve as a guide to possible weaknesses in the model. Higher values on the MIs may indicate the necessity of model respecification. Examples of substantive reasons for model respecification include situations when multiple items are used from a questionnaire and when those items contain similar wording or contain reverse wording, as well as reflections on the prior literature that support model modification (Brown, 2006). I cautiously applied each parameter respecification in case that: (a) there is a substantial size of its MI value compared with those of remaining parameters; (b) misspecification regarding the parameter for one group is replicated for other group; or (c) any modification of a model must be theoretically justifiable (Bryne, 2012).

Step 2: Testing the Equivalence of the Model

I conducted tests of measurement invariance across groups using MACS procedures recommended by Byrne (2012). The MACS procedures allow researchers to evaluate cross-group measurement equivalence by placing between-groups equality constraints on the factor loadings and the intercepts/thresholds in the measurement model. Specific steps which are necessary for testing cross-group measurement equivalence are described below. At every step of this procedure, I evaluated the fit of the model with constraints and the difference of its relative fit in comparison to the less restricted model.

Configural invariance. The first step is to measure the extent to which the measurement model fit the data adequately in each group. It is satisfied if the basic model structure, including the number of factors and the factor loading patterns, is invariant across groups (i.e., *configural invariance*). This model includes freely estimated parameters (i.e., factor loadings, thresholds, error variances, and covariances between constructs) in each group. Because there are no constraints on loadings or thresholds imposed across groups in a configural invariance model, the fit of this model serves as the baseline against which subsequent tests of invariance are made.

Metric invariance. In order to ensure that different groups respond to the items in the same way, the second step is to constrain factor loadings to be equal in all of the groups because the factor loadings carry the information about the relation between latent factors and observed indicators. This constrained model is compared with the unconstrained model (i.e., configural invariance model) assessed in the first step. If the fit of the constrained measurement model is still good and the statistical significance of the $\Delta\ \chi^2$ and/or the change in approximate fit statistics between the constrained and the unconstrained model (i.e., ΔCFI and ΔRMSEA) is acceptable, it indicates the metric equivalence of the measurement model across samples. In other words, the latent constructs are understood similarly in different groups. Dimitrov (2010) has supported asserting partial metric invariance in cases where less than 20% of factor loadings are nonequivalent across groups.

Scalar invariance. Lastly, I tested the model for *scalar invariance*. Scaler invariance implies that individuals who share a common score on a latent factor would have a similar probability of choosing a particular answer on an item regardless of group membership (Milfont & Fischer, 2010). The scalar invariance model constrains not only factor loadings but also item thresholds to be equal across groups. This more constrained model is compared with the less unconstrained model (i.e., metric invariance model) assessed in the second step. If the fit of the scalar invariance model is still good and the statistical significance of the $\Delta\ \chi^2$ and/or the change in approximate fit statistics between the the scalar invariance model and the metric invariance model (i.e., ΔCFI and ΔRMSEA) is acceptable, the scalar equivalence of the measurement model across samples is supported. This study employed the conservative recommendation of less than 20% noninvariant thresholds to claim a partial scalar invariance (Dimitrov, 2010).

Invariance model fit criteria. Following estimation of the configural model, invariance testings then continue with a sequence of progressively restrictive models. I constrained specific sets of parameters (i.e., constrained factor loadings for metric model and constrained thresholds for scalar invariance) to be equal across groups and evaluated fit statistics to determine if the specific parameters were invariant across groups.

The change in the χ^2 statistics per degrees of freedom (*df*) between a more constrained model and a less constrained model (calculated by the M*plus* DIFFTEST procedure) provides a direct comparison of model fit. A non-significant change in χ^2 indicated model fit was not significantly worsened by constraining the parameters to be equal across groups. It means the specific set of parameters being tested could be considered invariant across groups. However, χ^2 statistics are sensitive to sample size and model complexity (Chen, 2007). For these reasons, results are commonly interpreted with the other model fit indices (CFI and RMSEA). Cheung and Rensvold (2000, 2002) and Chen (2007) suggested that if the change in CFI (ΔCFI) is less than .01 and the change in RMSEA (ΔRMSEA) is less than .015, it means the change in model fit from the less constrained model to the more constrained model is neligible, indicating the more constraind model is acceptable.

Step 3: Examination of Mean Differences

Assuming the proposed measurement model is equivalent across groups, then, I examined mean-differences in latent constructs means across samples. In M*plus*, latent means are not directly estimated; rather, the latent mean for each group is estimated in reference to another group. In this dissertation study, I fixed the means of the Korean sample to zero in order to be the baseline sample against which the U.S. sample is then compared. In addition, I used Cohen's *d* effect size (Cohen, 1988) which was calculated using the following equation: $d = 2t / \sqrt{df}$, using the t-statistics provided in the M*plus* output (Sass, 2011). In general, effect size of 0.2 is regarded as small effect, 0.5 as medium effect, and 0.9 as large effect (Cohen, 1988).

Step 4: Testing the Fit of the Structural Model and Direct and Indirect Effects

The proposed structural model incorporates the baseline measurement model, a mediating variable and control variables, and structural equations between variables. In order to examine whether the structural model fits the data satisfactorily for both the Korean and U.S. sample, I first conducted a full SEM for each sample and a multi group SEM using the goodness-of-fit indices discussed above (Muthen & Muthen, 2012). Then, I conducted a multi-group SEM in order to examine hypothesized indirect and direct effects of motivational constructs on math intention for both the Korean and U.S. samples. To evaluate mediation hypotheses, the Model Indirect command in M*plus* Version 7 was applied. Direct pathways from motivational beliefs to math intention, from motivational beliefs to math performance, and from math performance to math intention were evaluated by the statistical significance of the estimated path coefficient that link between factors.

Step 5: Test of the Equivalence of the Structural Model

After testing significant direct and indirect effects, I tested for moderation effect of culture using a multiple group analysis approach. A multiple group SEM analysis was conducted to test whether the relations in the final structural model were the same for students from different cultural groups. That is, the analysis was done to examine between-group variation in hypothesized relations among the constructs. Unlike the tests of measurement invariance, there is no requirement or expectation that these relations would be equivalent across groups.

As recommended by Bowen and Guo (2012), the sequence of testing proceeded as follows. First, the fit of the proposed structural model with path coefficients to be freely estimated (i.e., a freely estimated model) was estimated. Next, the fit of the model in which all path coefficients were constrained to be equal across groups (i.e., a fully constrained model) was estimated. Then, the χ^2 value of this fully constrained model is then compared with the χ^2 value of freely estimated model. If the change in χ^2 between these two models is significant ($p < .05$), it means that the strength of at least one of the path coefficients was not equivalent across groups.

In order to identify the source of nonequivalence in the structural model, the paths were constrained in a stepwise fashion; the path producing the least amount of change in the χ^2 value (when compared with the fit of a freely estimated model) was first constrained followed by the path that leads to the second smallest difference in χ^2. The procedures were continued until all paths that produced a nonsignificant change in χ^2 when compared with a freely estimated model were included. If the $\Delta\chi^2$ is non-significant, it could be concluded the structural coefficients are equal across groups. When the $\Delta\chi^2$ is statistically significant ($p < .05$), those structural coefficients may vary across groups so a theory and/or the modification indices could be used in order to explain the nonequivalence of the relations.The DIFFTEST option was used to compute the appropriately adjusted χ^2 difference between models.

Summary of Research Hypotheses and Analytic Strategies

The hypotheses and analytic strategies are summarized as below. I presented the theoretical rationale for the following hypotheses in the Chapter 2 (see p. 41-43).

Hypothesis 1. I hypothesized that that the measurement model fits the data satisfactorily for both the Korean and U.S. samples using the following goodness-of-fit indices used for structural equation modeling in Mplus (Muthen & Muthen, 2012): Chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error Approximation Index (RMSEA).

Hypothesis 2. I hypothesized that the constructs of math self-concept, math interest, math utility, and math anxiety are equivalent across the U.S. and Korea samples. A series of measurement invariance tests (i.e., configural invariance, metric invariance, and scalar invariance) based on the analysis of means and covariance structures (MACS) are conducted.

Hypothesis 3. I hypothesized that compared to Korean students, U.S. students show higher level of math self-concept (Hypothesis 3.1), lower level of math interest (Hypothesis 3.2), lower level of math utility value (Hypothesis 3.3), and lower level of math anxiety (Hypothesis 3.4). The mean-differences of motivational constructs were tested through analysis of means and covariance structures (MACS).

Hypothesis 4. I hypothesized that that the structural model fits the data satisfactorily for both the Korean and U.S. samples using the following goodness-of-fit indices used for multiple group structural equation modeling in Mplus (Muthen & Muthen, 2012): Chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error Approximation Index (RMSEA).

Hypothesis 5. I hypothesized that there are direct relations between math self-concept (Hypotheses 5.1), math interest (Hypothesis 5.2), math utility (Hypothesis 5.3), and math anxiety (Hypothesis 5.4) and intention to pursue math in the future among both U.S. and Korean students. The multiple group SEM was used to test the hypothesized structural relations.

Hypothesis 6. I hypothesized that current math performance mediates the relations between math self-concept (Hypothesis 6.1), math interest (Hypothesis 6.2), math utility (Hypothesis 6.3), and math anxiety (Hypothesis 6.4) and intention to pursue math in the future. A multiple group SEM analysis was used to test the hypothesized structural relations.

Hypothesis 7. I hypothesized that the strength of some associations between constructs in the expectancy-value model varies across samples. A multiple group SEM analysis was conducted to test whether the relations in the model were quivalent for samples from different countries.

CHAPTER 4: RESULTS

This study examined the relations between math-related motivational beliefs, math performance, and intention to pursue math of Korean and U.S. adolescents. This chapter provides the results of the investigation in three parts. First, descriptive information is summarized. Next, results from testing the equivalence of the measurement model and an examination of mean differences are presented. Third, results from testing the hypothesized structural relations among the variables of interest and then testing the equivalence of the structural model are discussed. Findings are organized by research hypotheses. Lastly, a summary of results is provided.

Descriptive Statistics

The data used in this dissertation were nested, cross-sectional, secondary data of PISA 2012. Table 4.1 and Table 4.2 present the descriptive statistical information on the data used for estimating the measurement model including independent and dependent variables[6]. The means, standard deviations, and medians indicate the central tendency of each indicator. In addition, because these indicators are ordered categorical, information about the number of responses (i.e., percentages) in a particular response category is also contained in the tables.

In the previous method section, SEM assumptions including missing data, outliers, univariate normality and multicollinearity were discussed. In summary, the assumption of normality was upheld: even though there is various range of skew (-.38 to .55) or kurtosis (-2.00

[6] I already discussed descriptive statistical information on the mediating variable (math performance) and control variables in the Chapter 3.

to .32), none of the items exhibited extreme skewness or kurtotic tendencies. West, Finch, and Curran (1995) argued that an absolute (±) skew value of > 2 and a kurtosis value > 7 indicate a departure from normality. Next, small percentages of missing values, ranging from 0.2 % to 5.75%, were evident and these missing values were not *missing completely at random*. The missing data were handled using full information maximum likelihood (FIML) procedures in the analysis. There were also no pairs of items that displayed large bivariate correlations, which reached 0.85 or higher (Kline, 2011).

Table 4.1

Descriptive Statistics for Ordinal Indicators of Latent Factors: Korea

Variable	*N*	Mean	S.D	Median	% of response				Skewness (S.E=.06)	Kurtosis (S.E=.12)
					strongly disagree	disagree	agree	strongly agree		
Exogenous										
Not good at math (R)	1,685	2.37	.85	2.00	15.3	41.2	34.3	9.1	.10	-.61
Get good grades in math	1,685	2.14	.81	2.00	21.2	49.0	24.2	5.4	.36	-.32
Learn quickly	1,683	2.21	.77	2.00	16.3	51.8	26.6	5.0	.30	-.20
One of best subjects	1,683	2.12	.97	2.00	30.9	36.8	21.3	10.7	.47	-.78
Understand difficult work	1,683	1.95	.76	2.00	28.1	51.5	16.8	3.3	.53	.01
Enjoy reading about math	1,684	2.02	.81	2.00	27.6	46.7	21.1	4.2	.44	-.34
Look forward to lessons	1,684	1.91	.79	2.00	32.3	46.9	17.4	3.1	.55	-.18
Enjoy math	1,684	2.11	.90	2.00	27.2	41.7	23.1	7.7	.43	-.59
Interested in the things in math	1,684	2.38	.92	3.00	19.9	32.6	36.9	10.3	-.01	-.88
Worthwhile for work	1,685	2.56	.97	3.00	17.5	25.6	39.7	17.1	-.19	-.93
Worthwhile for career chances	1,684	2.60	.95	3.00	17.0	21.3	45.7	15.7	-.34	-.79
Important for future study	1,685	2.63	.96	3.00	15.7	23.1	42.5	18.4	-.30	-.83
Helps to get a job	1,684	2.47	.93	3.00	17.7	31.0	37.8	13.2	-.07	-.88
Worry that it will be difficult	1,686	2.95	.75	3.00	4.4	17.4	57.0	21.0	-.55	.32
Get very tense	1,685	2.23	.81	2.00	16.9	51.6	24.9	7.4	.39	-.24
Get very nervous	1,684	2.45	.83	2.00	11.4	42.8	35.2	10.3	.12	-.52
Feel helpless	1,684	2.37	.86	2.00	14.9	42.9	31.8	10.1	.17	-.60
Worry about getting poor grades	1,684	3.12	.85	3.00	5.8	12.2	46.2	35.5	-.82	.26
Endogenous					Other	Math				
Choose math courses after school	1,672	.40	.49	0.00	55.0	40.0			.39	-1.85
Study harder in math classes	1,672	.48	.50	0.00	51.5	47.5			.08	-2.00

Note. R= reversed coding for analysis; S.D= Standard Deviation; S.E= Standard Error

Table 4.2

Descriptive Statistics for Ordinal Indicators of Latent Factors: U.S.

Variable	*N*	Mean	S.D	Median	% of response				Skewness (S.E= .06)	Kurtosis (S.E= .12)
					strongly disagree	disagree	agree	strongly agree		
Exogenous										
Not good at math (R)	1,612	2.74	.91	3.00	11.9	21.0	45.6	19.1	-.43	-.57
Get good grades in math	1,612	2.97	.76	3.00	3.9	18.3	52.6	22.8	-.49	.06
Learn quickly	1,605	2.73	.87	3.00	8.0	29.5	40.4	19.2	-.20	-.66
One of best subjects	1,610	2.54	1.03	2.00	18.0	30.1	28.2	21.1	-.01	-1.12
Understand difficult work	1,611	2.50	.88	2.00	12.5	37.7	34.0	13.4	.06	-.72
Enjoy reading about math	1,628	2.21	.86	2.00	20.5	44.0	26.6	7.4	.30	-.54
Look forward to lessons	1,627	2.44	.90	2.00	14.7	39.2	31.5	13.0	.12	-.75
Enjoy math	1,622	2.34	.93	2.00	18.8	40.1	26.5	12.7	.25	-.79
Interested in the things in math	1,623	2.52	.90	2.00	12.9	36.6	33.9	14.9	.03	-.78
Worthwhile for work	1,624	3.03	.79	3.00	4.7	15.3	50.7	27.6	-.63	.15
Worthwhile for career chances	1,623	2.99	.83	3.00	6.4	14.3	51.6	25.9	-.69	.19
Important for future study	1,623	2.86	.90	3.00	8.4	22.3	41.9	25.6	-.43	-.58
Helps to get a job	1,618	2.99	.82	3.00	6.2	14.4	51.0	26.3	-.69	.18
Worry that it will be difficult	1,618	2.67	.85	3.00	7.9	32.6	40.8	16.6	-.12	-.62
Get very tense	1,607	2.34	.88	2.00	15.8	43.5	27.4	10.7	.27	-.60
Get very nervous	1,611	2.22	.81	2.00	16.5	50.8	22.9	7.3	.43	-.17
Feel helpless	1,606	2.08	.82	2.00	22.5	51.5	16.2	7.0	.62	.06
Worry about getting poor grades	1,615	2.51	.98	2.00	1.65	32.5	31.0	17.8	.01	-.99
Endogenous					Other	Math				
Choose math courses after school	1,558	.61	.49	1.00	36.5	57.8			-.46	-1.79
Study harder in math classes	1,561	.64	.48	1.00	33.8	60.7			-.60	-1.65

Note. R= reversed coding for analysis; S.D= Standard Deviation; S.E= Standard Error

Testing the Measurement Model

I conducted the following analysis in order to examine two sets of hypotheses: (a) the hypothesized measurement model would produce satisfactory goodness-of-fit indices (Hypothesis 1), and (b) the measurement model would be invariant across groups (Hypothesis 2). As discussed earlier in the Chapter 3 (see p. 73-74), evaluation of overall model fit was based on the χ^2 and the following combination of fit indices: cut-off values close to .95 for TLI and CFI indicate that the model provides a good fit to the data (Hu & Bentler, 1999). RMSEA value below .06 reflects an excellent fit (Hu & Bentler, 1999); that between .06 and .08 reflects a reasonable fit (Browne & Cudeck, 1993).

Measurement Model Specification- Establishing Baseline Model

Confirmatory factor analyses (CFAs) were conducted on the proposed five latent factors in order to examine whether individual indicator variables represented their latent factors (Hypothesis 1). This model was tested separately with each sample and modified in order to establish the final baseline model prior to testing the invariance of the measurement model.

For measurement model identification, in general, a latent factor needs at least three (just-identified) or more (over-identified) indicators (Brown, 2006)[7]. For this study, the overall measurement model was overidentified, meaning that the number of measured observations was greater than the number of parameters to be estimated (Kline, 2011). Each individual latent factor in the measurement model was also overidentified, except one latent factor (i.e., math

[7] The number of directed paths emitted by a latent variable is the key criterion rather than the number of indicators (Bollen & Davis, 2009). Thus, a latent factor which has two indicators can be identified when the following condition holds: the construct has two indicators whose errors are uncorrelated and either "both the indicators of the construct correlate with a third indicator of another construct but neither of the two indicators' errors is correlated with the error of that third indicator", or "the two indicators' loadings are set equal to each other" (Kenny, Kashy, & Bolger, 1998, p. 253).

intention having two indicators). Thus, instead of testing each factor separately, CFAs of the full measurement model were tested through allowing them to correlate. Muthén (2001) suggested that even though each part of the measurement model cannot be identified due to the lack of indicators when analyzed alone, it could be identified when it is part of a larger model. At this point, no structure is imposed on the relations between latent variables and all variables were allowed to correlate.

The results showed that the resulting model illustrated the following fit statistics: for the Korean sample, χ^2 [df = 160, N = 1,689] = 2781.95, p < .001, RMSEA = .099 (90% CI (.096 - .102)), CFI = .946, and TLI = .936; for the U.S sample, χ^2 [df = 160, N = 1,652] = 1434.01, p < .001, RMSEA = .070 (90% CI (.066 - .073), CFI = .981; and TLI = .978. To summarize, for the Korean sample, CFI suggested adequate fit but other fit statistics of the model were not acceptable. For the U.S. sample, the model displayed adequate fit statistics for the CFI and TLI but a fair/reasonable fitting RMSEA value.

Next, I considered an alternative model using information from modification indices (MIs). Each parameter respecification was cautiously applied only in case that: (a) there is a substantial size of its MI value compared with those of remaining parameters; (b) misspecification regarding the parameter for one group is replicated for other group; or (c) any modification of a model must be theoretically justifiable (Bryne, 2012). Following Bryne's (2012) guideline, only one parameter at a time was changed and the respecified model was tested and evaluated if the change provided a good fit to the data.

An inspection of the MIs suggested that several large MI values were found for both the Korean and U.S. samples. One of the large misspecified parameter was the cross-loading of item ST42Q02 (i.e., "I am not good at math") on Math Anxiety factor, in addition to its targeted Math

Self-Concept factor. Based on the previous findings, the item may be not useful for identifying math anxiety due to the negative-item method effect. Chiu (2008) reported negative-item method effect for the two negatively worded self-concept items for the TIMSS 2003 data. Chiu noted that the factor loadings for these items were systematically lower than for the positively worded items and suggested that, "items that are negatively worded appear to be unreliable in cross-cultural studies" (p. 251). Based on the substantial size of the parameter's MI value as well as theoretical justification, I excluded the item in the analysis and then re-estimated the model. Results led to some improvement in fit: for the Korean sample, χ^2 [df = 142, N = 1,689] = 2449.67, p < .001, RMSEA = .098 (90% CI (.095 -.102)), CFI = .951, and TLI = .941; for the U.S sample, χ^2 [df = 142, N = 1,652] = 858.32, p < .001, RMSEA = .055 (90% CI (.051 - .059); CFI = .988 and TLI = .986.

Next, another larger misspecified value involved the item ST42Q10 (i.e., "I worry about getting poor grades in math") that was highly loaded on Math Utility Value factor other than the factor intended (Math Anxiety), indicating that a large proportion of the variance in this item is accounted for by the other latent variable. The finding suggested that the item may be not uniquely associated with the hypothesized factor (Math Anxiety); thus, it is not as useful in identifying discrete dimension of math anxiety. Especially for the Korean sample, the item had a low item-to-subscale correlation (r = .38) as well as the smallest loading on Math Anxiety factor, with a standardized estimate of .25, suggesting problems with use of the item. The cross-loading of ST42Q10 was also occurred for the U.S. sample and the size of MI was still high. Thus, I excluded the item in the analysis and then re-estimated the model. Results led to some improvement in fit: for the Korean sample, χ^2 [df = 125, N = 1,689] = 1613.61, p < .001, RMSEA = .082 (90% CI (.079 - .086)), CFI = .969, and TLI = .961; for the U.S sample, χ^2 [df =

125, N = 1,652] = 781.28, p < .001, RMSEA= .055 (90% CI (.051 - .059), CFI = .989, and TLI = .987.

In addition, an inspection of MI_S revealed that for the Korean sample, there remained a large residual covariance between ST42Q03 (i.e., “I get very tense when I have to do mathematics homework”) and ST42Q05 (i.e., “I get very nervous doing mathematics problems”). Such a residual covariance may result from overlapping item content. Hence, I allowed the error term associated with these two items to correlate. Results led to some improvement in fit: for the Korean sample, χ^2 [df = 124, N = 1,689] = 1118.56, p < .001, RMSEA =.069 (90% CI (.065 - .073), CFI = .979, and TLI = .974. Because there was little improvement in fit for the U.S. sample (χ^2 [df = 124, N = 1,652] = 774.91, p < .001, RMSEA =.055 (90% CI (.051 - .059), CFI = .989, and TLI = .987), I decided to include correlated errors between indicators only for the Korean sample, not for the U.S. sample. Bryne (2012) argued that in order to proceed to multiple group modeling, the pattern of factor loadings should be the same across groups, however, correlated errors between indicators can be presented differently across groups.

In summary, for establishing the baseline measurement model, I omitted ST42Q02 and ST42Q10 and allowed the error term associated with ST42Q03 and ST42Q05 which was indicated by a bidirectional arrow in the *Figure 4.1* only for the Korean sample. The revised baseline measurement model (*Figure 4.1*) had good fit: for the Korean sample, χ^2 [df = 124, N = 1,689] = 1118.56, p < .001, RMSEA =.069 (90% CI (.065 - .073), CFI = .979, and TLI = .974; for the U.S. sample, χ^2 [df = 125, N = 1,652] = 781.29, p < .001, RMSEA= .055 (90% CI (.051 - .059), CFI = .989, and TLI = .987. Although the χ^2 statistic was significant for each group model, this finding was expected given the large sample size of the study. Pre-established criteria for each of the practical fit indices (i.e., CFI, TLI, and RMSEA) were met for the model.

The CFA result for each sample indicated that standardized factor loadings for each of the 16 items on their respective latent factor were all positive and statistically significant ($p < .001$), with standardized loadings ranging from .66 to .95 for Korean sample except ST42Q05[8] and from .80 to .93 for U.S sample. Correlations between factors were moderate-to-strong ranging from $r = -.37$ to $r = .81$ (see Table 4.3).

Table 4.3

Intercorrelations among Latent Variables

	MSC	MIV	MUV	MA	MI
Math Self Concept (MSC)	1.00	.73	.52	-.77	.59
Math Interest Value (MIV)	.80	1.00	.71	-.53	.57
Math Utility Value (MUV)	.62	.81	1.00	-.39	.54
Math Anxiety (MA)	-.71	-.60	-.37	1.00	-.49
Math Intention (MI)	.72	.79	.74	-.50	1.00

Note. The upper diagonal is for the U.S. sample and the lower diagonal is for the Korean sample.

Summary of CFA result. The revised measurement model (*Figure 4.1*) had good fit for each country group. Each latent factor of motivational beliefs included four item scales and intention to pursue in the future included two items. A correlation among the error for ST42Q03 and ST42Q05 was included in the measurement model only for the Korean sample. Given the evidence of good model fit across the cultural groups, the model was retained as the baseline for subsequent measurement invariance testing.

[8] ST42Q05 has relatively lower factor loading (.37) compared to other items, however, the value has been acceptable by previous studies (e.g., Cook, Eignor, Steinberg, Sawaki, & Cline, 2014). In addition, Muthén (2006) argued that there is no golden standard cutoff for the size of factor loadings so their significance is more important to be considered.

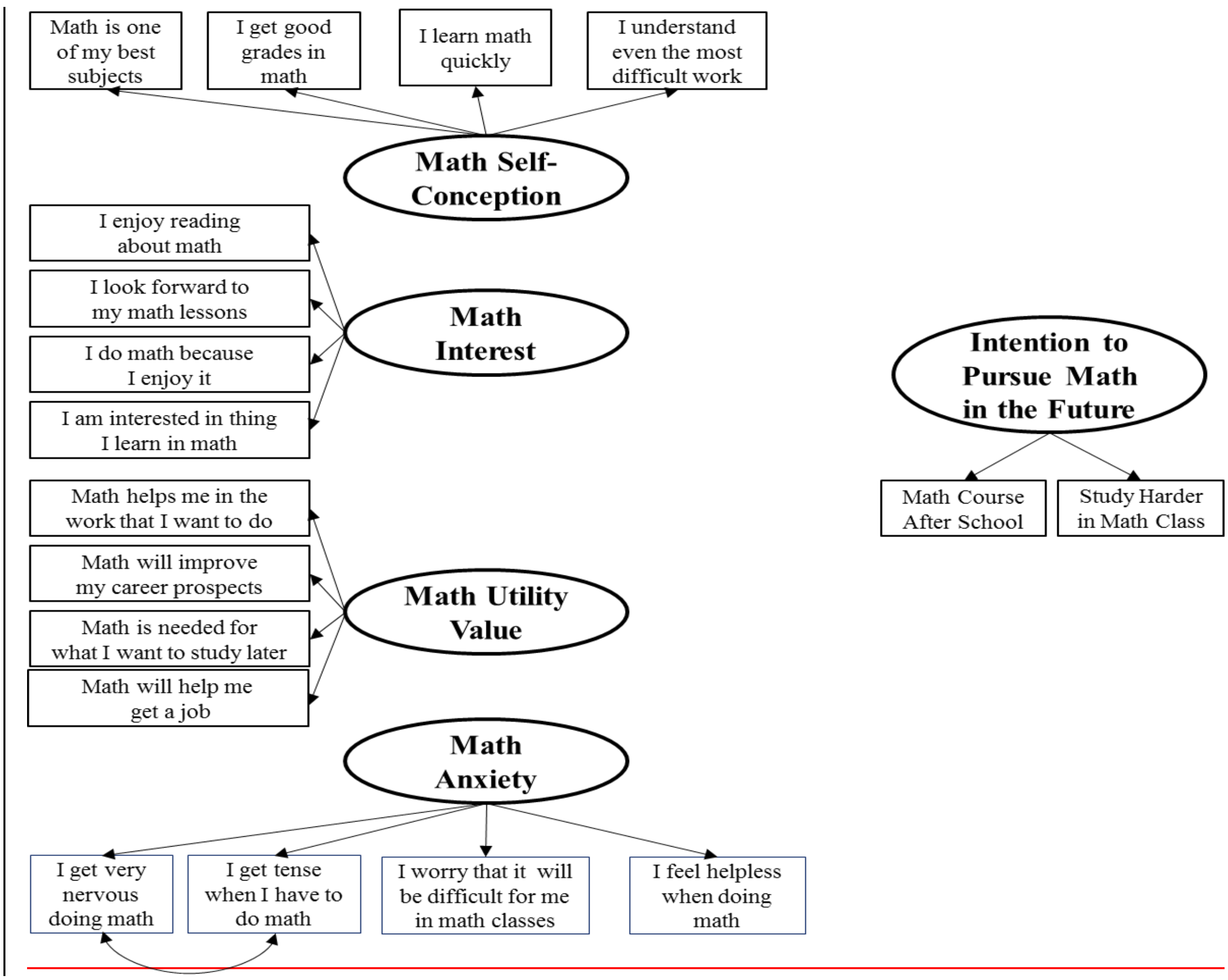

Figure 4.1 A Revised measurement model

Note. Double arrow is only for the Korean sample. All variables were allowed to correlate, but correlations between factors are not shown in this figure for the sake of simplicity.

Measurement Invariance

With the establishment of well-fitting baseline model for each group, analysis turned to tests of measurement invariance to determine whether the items performed equivalently across groups (Hypothesis 2). The main focus of second research question is to examine the construct comparability for motivational beliefs latent factors. However, I tested all latent factors including Math Intention together because CFA analyses earlier were conducted on the factors as a group. MACS approach was used for testing measurement invariance. All measurement invariance models were estimated with the WLSMV estimator and THETA parameterization.THETA parameterization is highly recommended in a multigroup anlaysis because it provides information on residual variances (i.e., unexplained variance in the observed indicators of factors; Millsap & Yun-Tein, 2004).

In order to establish measurement invariance measurement, the following sequence of models was tested: (a) *configural invariance* model (i.e., a same model is estimated for each group simultaneously but all factor loadings and thresholds are freed to vary across groups), (b) *metric invariance* model (i.e., all factor loadings are constrained across groups), and (c) *scalar invariance* model (i.e., all factor loadings and thresholds are constrained across groups). The fit of the more constrained model is compared with the previous model to determine whether the more constrained model should be accepted, rejected, or revised (Millsap & Yun-Tein, 2004). The factor variance was fixed to 1 and the factor mean was fixed to 0 in each group for identification. Table 4.5 represents a comprehensive summary of the findings associated with the estimation of models to evaluate measurement invariance.

Testing configural invariance. A configural invariance model tested whether the basic factor structure of the model was invariant across groups. The fit of the initial unconstrained model (M1 in Table 4.5) – all factor loadings and thresholds freed to vary across groups – was good: χ^2 [df = 249, N = 3,341] = 1852.15, p < .001, RMSEA =. 062 (90% CI (.060 - .065), CFI =. 984, and TLI = .981, suggesting that the hypothesized measurement model represented a good fit to the data across groups. The result supported full configural invariance of the proposed measurement model so that the model could serve as the basis for comparison for subsequent invariance models (Milfont & Fischer, 2010).

Testing metric invariance. Next, I tested the metric invariance of the measurement model. . A well-fitting metric model (M2 in Table 4.5) indicates that the strengths of the relations between indicators and their corresponding factors do not vary significantly across groups. Full metric invariance was tested by constraining all of the factor loadings to be equal across groups. The fit of this full constrained model was not adequate: χ^2 [df = 267, N = 3,341] = 3245.31, p < .001, RMSEA = .082 (90% CI (.079 - .084)), CFI = .971, and TLI = .967. Based on the M*plus* DIFFTEST, the decrement in fit from the configural invariance model to the metric invariance model was significant ($\Delta\chi^2$ [Δdf = 18] = 784.26, p < .001). In addition, the difference in fit indices was beyond the cutoff; ΔCFI = -.012, ΔRMSEA =.020. It means that the magnitude of some factor loadings varied significantly across samples.

Byrne, Shavelson and Muthen (1989) argued that full metric invariance was not always necessary to do further tests of invariance and substantive analyses including comparisons of factor means. As well, full metric invariance is ideal but sometimes unrealistic in cross-cultural studies (Horn & McArdle, 1992). Thus, as a follow-up probing of metric invariance test, a partial metric invariance model (M3 in Table 4.5), in which some parameters were allowed to be freely estimated, was tested. MIs were used to determine which cross-group equality constraints could be released to improve model fit (Bryne, 2012). It revealed one localized area of noninvariance across groups: the loadings for item ST42Q05 (“I get nervous doing math”). In other words, Korean students and U.S students might have responded differently to the individual item of ST42Q05. Examination of the magnitude of the standardized factor loading estimates showed that the factor loading for item ST42Q05 was substantially lower for Korean (λ=.28) than the loading for U.S sample (λ=.70).

Although χ^2 difference between a new partial metric invariance (M3 in the Table 4.5) and configural invariance was significant ($\Delta\chi^2$ [Δdf = 17] = 344.17), the difference in model fit indice is minimal (ΔCFI = -.001, ΔRMSEA = .003). In addition, the fit of a partial constrained model was adequate: χ^2 [df = 266, N = 3,341] = 2155.02, p < .001; RMSEA = .065 (90% CI (.063 - .068)), CFI = .982, and TLI = .980. Thus, the partial metric invariance model was supported, so I continued to test a scalar invariance (Byrne, 2012).

Testing scalar invariance. In the scalar invariance model (M4 in Table 4.5), in addition to constraining the factor loadings to be equal, the *thresholds* of each indicator in the measurement model were equally constrained. The model fit of the fully constrained model was found to be acceptable but not good, χ^2 [df = 316, N = 3,341] = 4102.66, p < .001; RMSEA = .085 (90% CI (.083- .087)), CFI = .965, and TLI = .966. When the χ^2 difference test between the partial metric invariance model (M3) and the full scalar invariance model (M4) was computed, the increase in χ^2 was significant ($\Delta\chi^2$ [Δdf = 50] = 1558.21), which represented significant deterioration in model fit. In addition, the difference in fit indice was beyond the cutoff; ΔCFI = -.018, ΔRMSEA = .020. Thus, a full metric invariance model cannot be acceptable so that a partial scalar invariance model should be considered.

Steenkamp and Baumgartner (1998) argued that when a partial metric invariance is obtained, a partial scalar invariance is expected to be tested by allowing the thresholds of metrically noninvariant item (ST42Q05 in the current study) to be freely estimated. So, first, I allowed ST42Q05$2 and ST42Q05$3 to be freely estimated. The result showed that the DIFFTEST produced a significant χ^2 difference ($\Delta\chi^2$ [Δdf = 48] = 1467.79) and the difference in fit indice was beyond the cutoff (ΔCFI = -.017, ΔRMSEA = .019, see M5 in Table 4.5).

Examination of MIs revealed that besides two thresholds which were already unconstrained in the M5 in Table 4.5, six of the 50 thresholds (16%) could not be fully invariant across groups (Table 4.4). Freely estimating these eight constraints yielded a substantial and highly significant improvement in fit (see M6 in Table 4.5). The result of a χ^2 difference test between a partial scalar invariance model (M6) and a partial metric invariance model (M3) showed significant increase of the χ^2 ($\Delta\chi^2$ [Δdf = 42] = 1002.06), however, the difference in practical fit indices is acceptable: ΔCFI = -.008, ΔRMSEA = -.010. This partial scalar invariance model has also acceptable model fit: χ^2 [df = 308, N = 3,341] = 3264.67, p < .00, RMSEA = .075(90% CI (.073- .078)); CFI = .975, and TLI = .974.

Table 4.4

Values of Partially Noninvariant Thresholds

Factor	Threshold	Threshold Values	
		Korean	U.S.
Math Self Concept	ST42Q04$2	0.46	-0.83
	ST42Q04$3	1.51	0.66
	ST42Q06$2	0.41	-0.37
	ST42Q06$3	1.56	0.78
Math Interest	ST29Q03$2	0.78	0.11
Math Utility Value	ST29Q08$2	-0.08	-0.81
Math Anxiety	ST42Q05$2	0.11	0.58
	ST42Q05$3	1.27	1.53

Final measurement model. The final measurement model was specified based on results of the invariance testing and the supplemental analysis of statistical impact of noninvariance.

Overall, the partial measurement invariance was supported for the measurement model employed in the current study. The model is fully configural invariant, partially metric invariant, and partially scalar invariant. Nearly all factor loadings were invariant across groups; one exception was item ST42Q05 in the Math Anxiety factor. The loading of ST42Q05 was freely estimated across groups in the final measurement model. Eight out of 50 thresholds were partially noninvariant across groups. As discussed, a partial scalar invariance model, in which the eight thresholds were freely estimated across groups, showed an adequate model fit. Table 4.6 reports the unstandardized and standardized factor loadings in the final measurement model. All individual items loaded moderately and significantly on the hypothesized factors ($p < .001$), with standardized factor loadings ranging from .26 to .97.

The current study assumed that a partial scalar invariance is adequate for establishing justification for the cross-group comparisons of latent means (Bryne, 2012). Steenkamp and Baumgartner (1998) also argued that “metric and scalar invariance for at least two items per construct is required if the goal is to conduct comparisons of means across countries” (p. 82). However, because there has been still some controversy about whether a *strong factorial invariance* (i.e., full scalar invariance as well as full configural and metric invariance) is necessarily required to conduct cross-national comparisons of means, I note that mean differences in the current dissertation should be interpreted with caution.

Table 4.5

Summary of Testing of Invariance of the Measurement Model across Samples

	Model Fit					Invariance Testing				
Invariance	χ^2	*df*	CFI	TLI	RMSEA (90% CI)	Comparison	$\Delta\chi^2$	Δdf	ΔCFI	ΔRMSEA
M1: Configural	1852.15***	249	.984	.981	. 062 (.060 - .065)					
M2: Full Metric	3245.31***	267	.972	.967	.082 (.079 - .084)	M1	784.26***	18	-.012	.020
M3: Partial Metric	2155.02***	266	.983	.980	.065 (.063 - .068)	M1	346.99***	17	-.001	.003
M4: Full Scalar	4102.66***	316	.965	.966	.085 (.083 - .087)	M3	1558.21***	50	-.018	.020
M5: Partial Scalar	3984.50***	314	.966	.967	.084 (.081 - .086)	M3	1467.79***	48	-.017	.019
M6: Partial Scalar	3264.67 ***	308	.975	.974	.075 (.073 - .078)	M3	1002.06***	42	-.008	.010

Note. $\Delta\chi^2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.

$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$

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Table 4.6

Unstandardized and Standardized Factor Loading for Latent Constructs

	Unstandardized loading	Standardized loading	
		Korean	U.S.
Math Self- Concept			
ST42Q04	1.00[a]	0.85	0.81
ST42Q06	0.86	0.81	0.90
ST42Q07	1.15	0.88	0.90
ST42Q09	0.94	0.83	0.86
Math Interest			
ST29Q01	1.00[a]	0.85	0.81
ST29Q03	0.81	0.80	0.90
ST29Q04	1.69	0.94	0.95
ST29Q06	1.58	0.93	0.94
Math Utility Value			
ST29Q02	1.00[a]	0.90	0.88
ST29Q05	0.87	0.87	0.92
ST29Q07	1.10	0.91	0.91
ST29Q08	0.90	0.88	0.89
Math Anxiety			
ST42Q01	1.00[a]	0.72	0.82
ST42Q03	0.91	0.68	0.86
ST42Q05	0.26/ 0.70	0.26	0.80
ST42Q08	1.53	0.84	0.85
Math Intention			
ST48Q01	1.00[a]	0.94	0.96
ST48Q03	1.47	0.97	0.70

Note. The unstandardized values were constrained equal (except item ST42Q05) and therefore identical for the two groups. [a] indicates unstandardized factor loading fixed at one for model identification. All loadings were significant at $p < .001$.

Summary of measurement invariance results. Results revealed that partial measurement invariance was supported for the proposed measurement model. The model displayed configural invariance, but results revealed noninvariance for one factor loading. In addition, noninvariance was indicated for eight thresholds associated with five items. Following recommendations in the literature (Bryne, 2012; Byrne et al., 1989), the study found that the scales of measuring motivational constructs and math intention demonstrates sufficient measurement invariance to permit cross-group comparisons on each of the three latent variables as well as subsequent analysis.

Testing for Latent Means Difference

Table 4.7 presents the result of latent mean difference tests. Korean students served as the reference group in the comparison. The results showed that Korean adolescents were lower on most of the latent factors relative to their U.S. counterparts. As predicted, Korean students showed lower math self-concept. However, Korean students also reported lower interest value and utility value than the U.S. participants. Only math anxiety appeared higher for the Korean sample compared to the U.S sample.

Because absolute values of latent means can only be interpreted relative to the reference group in which the mean was fixed, Cohen's *d* was also used in order to determine practical relevance of results (see Table 4.7). In general, effect size of 0.2 is regarded as small effect, 0.5 as medium effect, and 0.9 as large effect (Cohen, 1988). The results showed small effect sizes (small standardized mean differences) for Math Interest, Math Utility Value, and Math Anxiety, and medium effect size for Math Self-concept and Math Intention.

Table 4.7

Latent and Raw Means for the Latent Factors

Latent construct	Korea		U.S.		Cohen's *d*
	Latent Mean	Raw	Latent Mean	Raw	
Math Self Concept	0.00	2.10	0.64***	2.69	0.66
Math Interest	0.00	2.11	0.26***	2.37	0.26
Math Utility Value	0.00	2.57	0.45***	2.97	0.44
Math Anxiety	0.00	2.50	-0.27***	2.33	0.29
Math Intention	0.00	0.49	0.53***	0.63	0.55

Note. Latent means are relative to Korea, which is set to zero. $^{***}p < .001$

Test of the Full Structural Equation Model

Next, in order to test the full structural model, I conducted the following analysis in order to examine four sets of hypotheses: (a) hypotheses that examined if the model fit the data satisfactorily, (b) hypotheses that explored direct effects (X→Y), (c) hypotheses that explored indirect effects (X→M→Y), and (d) hypotheses that explored whether the significant relations between variables were equivalent across groups. Math performance (PV1 - PV5) represented mediators in the model. This study tested five separate models for each plausible value variable; each model was identical with the exception of the plausible value. I report only the estimates for the first plausible value (PV1). Information on estimates for other plausible values is provided in the Appendix. The fit of the full model (*Figure 4.2*), inclusive of measurement and structural components, was evaluated with the goodness-of-fit indices applied in the test of the measurement model. In addition, the path coefficients that represented associations between latent variables were examined for magnitude and significance of the associations.

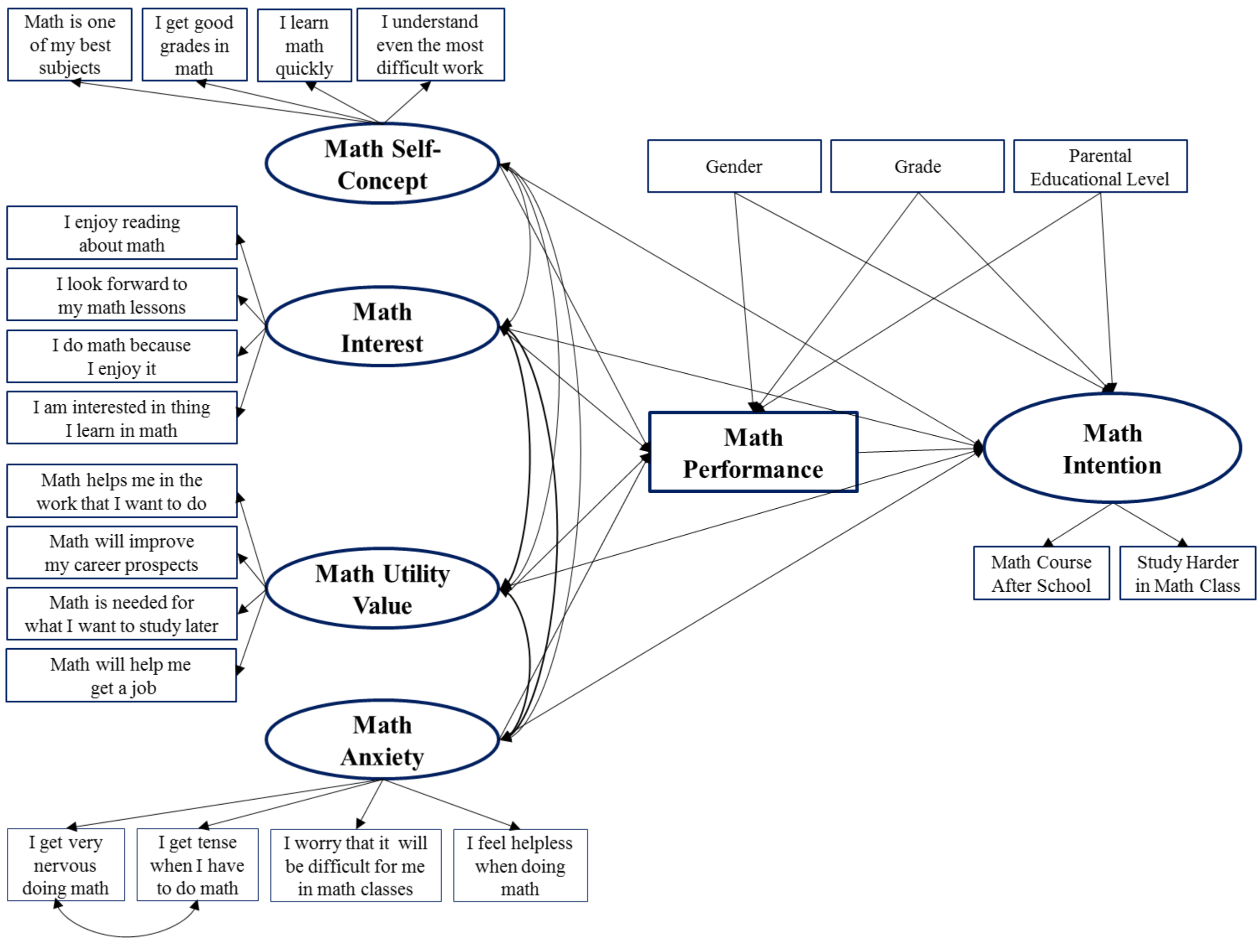

Figure 4.2 A Full structural equation model

Note. Double arrow is only for the Korean sample. All variables were allowed to correlate, but correlations between factors are not shown in this figure for the sake of simplicity

Overview of SEM Result

First, I tested the full structural model (*Figure 4.2*) in each sample in order to examine if the model fit the data satisfactorily (Research question 4). The results showed that the model fit was acceptable for the Korean sample: χ^2 [df = 188, N = 1,689] = 977.25, p < .001, RMSEA = .050 (90% CI (.047 - .053)), CFI = .985, and TLI = .982. For the U.S. sample, the model fit was excellent: χ^2 [df = 189, N = 1,652] = 686.36, p < .001, RMSEA = .040 (90% CI (.037 - .043)), CFI = .992, and TLI = .990. Results were similar for other plausible values. Overall, analyses indicated that the model fit the data satisfactorily in both countries.

Next, I conducted a multiple group SEM to evaluate the nature of the structural relations in the model across groups. A model fit was tested with the same model tested above in which all structural path coefficients were freely estimated across groups. Except for one factor loading and eight thresholds that were relaxed to reflect findings of partial metric and scalar invariance across groups, default constraints for multiple group models in M*plus* were maintained.

The overall model fit was acceptable: χ^2 [df = 408, N = 3,341] = 1714.67 (Korean contribution to χ^2 = 991.43, U.S. sample contribution to χ^2 = 723.23), p < .001, RMSEA = .044 (90% CI (.042 - .046)), CFI = .989, and TLI = .988. The R^2 estimates in this model indicated that the study variables explained 33% of the variance in the math performance scores for Korean students (32% for the U.S. sample) and 60% of the variance for Korean students (47% for the U.S. sample) in the intention to pursue math in the future for the overall sample. Results were similar for other plausible values.

Exploring Direct and Indirect Effect

Next, I explored if there were significant direct and indirect effects for the variables for the Korean and U.S. sample using a multiple group SEM analysis. I hypothesized that there would be direct relations between (a) math self-concept and math intention (Hypothesis 5.1), (b) math interest and math intention (Hypothesis 5.2), (c) math utility value and math intention (Hypothesis 5.3), and (d) math anxiety and math intention (Hypothesis 5.4) for both the Korean and U.S. sample. In addition, I hypothesized that math performance would mediate these relations (Hypotheses 6.1 to 6.4) for both the Korean and U.S. sample. Direct and indirect effects were estimated with the Model Indirect command in M*plus.*

Table 4.8 provides the result of standardized direct, indirect, total effects. For the Korean sample, I found a statistically significant positive direct effect of Math Self-Concept (Hypothesis 5.1, $p < .01$), a statistically significant positive direct effect of Math Interest (Hypothesis 5.2, $p < .001$), a statistically significant positive direct effect of Math Utility Value (Hypothesis 5.3, $p < .001$) on Math Intention. That is, Korean students who have higher level of math self-concept, math interest, and math utility value are more likely to have higher level of math intention. Similarly, for the U.S. sample, I found a statistically significant positive direct effect of Math Self-Concept (Hypothesis 5.1, $p < .001$), a statistically significant positive direct effect of Math Interest (Hypothesis 5.2, $p < .05$), and a statistically significant positive direct effect of Math Utility Value (Hypothesis 5.3, $p < .001$) on Math Intention. That is, U.S. students who have higher level of math self-concept, math interest, and math utility value are also more likely to have higher level of math intention. For both sample, there was no statistically significant direct effect of Math Anxiety on Math Intention (Hypothesis 5.4, $p = .54$ for the Korean sample and $p = .51$ for the U.S sample).

Results for indirect effects showed evidence for one partially mediated path and one fully mediated path for the U.S. sample. Full mediation occurs when researchers find a significant indirect effect and no presence of a significant direct effect. On the other hand, when the direct effect is still significant after controlling the indirect effect, the mediator was partially mediated the relation between X →Y (Rucker, Preacher, Tormala, & Petty, 2011). First, math performance partially mediated the pathway between math self- concept and math intention (Hypothesis 6.1, $p < .05$). Second, math performance fully mediated the relation between math anxiety and math intention (Hypothesis 6.4, $p < .05$).There were no indirect effects of math interest on math intention (Hypothesis 6.2) and of math utility value on math intention (Hypothesis 6.3).

For the Korean sample, I did not identify any predicted indirect effects. There were no indirect effects of math self- concept (Hypothesis 6.1), math interest (Hypothesis 6.2), and math utility value on math intention (Hypothesis 6.3), and math anxiety (Hypothesis 6.4) on math intention. Results were similar for other plausible values. Additional information is provided in Appendix A and B.

Table 4.8

Standardized Direct, Indirect, Total Effects for Math Intention

	Korea			U.S.		
	Direct	Indirect	Total	Direct	Indirect	Total
Predictor						
Math Self-Concept	0.14^{**}	0.02	0.16^{**}	0.24^{***}	0.03^{*}	0.27^{**}
Math Interest	0.31^{***}	0.00	0.30^{***}	0.13^{*}	-0.02	0.11
Math Utility Value	0.29^{***}	0.01	0.30^{***}	0.30^{***}	0.01	0.31^{***}
Math Anxiety	-0.06	0.00	-0.06	-0.06	-0.04^{*}	-0.09
Covariate						
Gender	0.16^{*}	0.00	0.16^{*}	0.01	0.02^{*}	-0.02
Grade	0.01	-0.00	0.02	0.13^{***}	0.01	0.13^{***}
Parental Education	0.06	-0.00	0.05	0.05	0.02^{**}	0.07^{**}

Note. The result was from a multigroup SEM. Math performance was measured by PV1.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Table 4.9 showed standardized and unstandardized direct pathway estimates for study variables and covariates for the U.S. and Korean samples. Here, I summarized the result of the relations (a) between four motivational beliefs and math intention (direct effect; $X \rightarrow Y$), (b) between four motivational beliefs and math performance (indirect effect; $X \rightarrow M$), and (c) between math performance and math intention (indirect effect; $M \rightarrow Y$). In addition, results related to covariates are also summarized.

Motivational beliefs and math intention. For both Korean and U.S. sample, I found the significant positive standardized path coefficient of Math Self-Concept (γ = .14 for the Korean sample, γ =.24 for the U.S. sample), Math Interest (γ= .31 for the Korean sample, γ =.13 for the U.S. sample), and Math Utility Value (γ = .29 for the Korean sample, γ =.30 for the U.S. sample) on math intention. The hypothesized direct path between Math Anxiety and Math Intention was not significant for both groups.

Motivational beliefs and math performance. For the Korean sample, I found significant positive standardized path coefficient of Math Self-Concept (γ = .39) and Math Utility Value (γ = .25) on Math Performance. There were no direct pathways between Math Interest and Math Performance as well as between Math Anxiety and Math Performance for the Korean sample. For the U.S. sample, I found a significant positive standardized path coefficient of Math Self-Concept on Math Performance (γ = 27) and a significant negative standardized path coefficient of Math Anxiety value on Math Performance (γ = -.36). There were no direct pathways between Math Interest and Math Performance as well as between Math Utility Value and Math Performance for the U.S. sample.

Math performance and math intention. For the Korean sample, I found no significant path coefficient for Math Performance on Math Intention. On the other hand, for the U.S.

sample, there was a significant positive standardized path coefficient of Math Performance on Math Intention ($\gamma = .10$). That is, if U.S. adolescents have higher level of math performance, they are more likely to show higher intention to pursue math in the future.

Covariates. In addition to the main variables of interest, several covariates were included in the model to control for their effect on math performance and math intention. Students' gender was significantly associated with Math Performance ($\gamma = .10$ for the Korean sample, $\gamma = .06$ for the U.S. sample, $p < .001$) and Math Intention ($\gamma = .16$ for the Korean sample, $\gamma = .13$ for the U.S. sample, $p < .001$), suggesting that being female was associated with higher levels of math performance and intention to pursue in the math. Grade level was significantly related with only Math Performance ($\gamma = .09$ for the Korean sample, $\gamma = .24$ for the U.S. sample, $p < .001$). That is, a higher grade is associated with higher level of math performance. Likewise, parental education level was significantly related with only Math Performance ($\gamma = .21$ for the Korean sample, $\gamma = .26$ for the U.S. sample, $p < .001$). When students have parents with higher educational level, they are more likely to show higher level of math performance.

Table 4.9

Standardized and Unstandardized Direct Pathway Estimates for Study Variables and Covariates

	Korean sample			U.S sample		
Structural Path	unstandardized	standardized	*p*-value	unstandardized	standardized	*p*-value
Math Self Concept → Math Intention	.24 (.11)	.14 (.09)	.00	.18 (.14)	.14 (.09)	.00
Math Interest → Math Intention	.50 (.19)	.31 (.12)	.00	.20 (.10)	.13 (.07)	.02
Math Utility Value → Math Intention	.36 (.08)	.29 (.05)	.00	.41 (.07)	.30 (.05)	.00
Math Anxiety→ Math Intention	-.16 (.12)	-.06 (.04)	.18	-.06(.09)	-.06 (.03)	.32
Math Self concept → Math Performance	.23 (.04)	.39 (.09)	.00	.24 (.05)	.27 (.05)	.00
Math Interest → Math Performance	-.06 (.04)	-.01(.12)	.18	-.10 (.04)	-.06 (.05)	.08
Math Utility Value → Math Performance	.11 (.02)	.25 (.06)	.00	.04 (.03)	.05 (.03)	.32
Math Anxiety→ Math Performance	.01 (.08)	-.01 (.05)	.21	-.31 (.04)	-.35 (.04)	.00
Math Performance → Math Intention	.05 (.05)	.04 (.03)	.19	.19 (.07)	.10 (.04)	.00
Gender → Math Intention	.83 (.19)	.16 (.03)	.00	.34 (.09)	.13 (.03)	.00
Grade → Math Intention	.01 (.37)	.01 (.04)	.80	-.05 (.09)	-.01 (.03)	.63
Parental Education→ Math Intention	.05 (.04)	.04 (.04)	.24	.02 (.02)	.05 (.04)	.09
Gender → Math Performance	.37 (.07)	.10 (.03)	.00	.11 (.05)	.06 (.03)	.00
Grade → Math Performance	.20 (.14)	.09 (.04)	.00	.39 (.05)	.24 (.03)	.00
Parental Education→ Math Performance	.09 (.01)	.21 (.03)	.00	.09 (.01)	.26 (.03)	.00

Note. The result was from a multigroup SEM. Math performance was measured by PV1. unstandardized = unstandardized parameter coefficient; standardized = standardized parameter coefficient

Equivalence of the Structural Relations across Groups

I tested hypotheses concerning the equivalence of the structural paths across samples (Research Question 7). In order to examine whether pathways differed between Korean and U.S. samples, I utilized a multiple group comparison approach. In conducting the multiple group analysis, I took an iterative, step-wise approach and used the differences in χ^2 to compare the models (Bowen & Guo, 2012; Byrne, 2012). Assessing the differences in χ^2 is a recommended approach for comparing nested structural equation models (Bollen, 1989; Byrne, 2012). Here, one by one each pathway was constrained and χ^2 difference test was performed to examine whether there are statistically significant χ^2 changes at $p \leq 0.05$ between the unconstrained model and the constrained model. If adding a constraint to the model (i.e., a constrained model) produces a statistically significant change in χ^2 when comparing with unconstrained model, I can conclude that the culture/nationality moderates the path (Bowen & Guo, 2012). A model comparison was conducted by utilizing the DIFFTEST option in M*plus*, which appropriately adjusted for WLSMV estimation. All pathways in the model (15 total) were tested, even those that were non-significant in the full model.

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First, the simultaneous test of the hypothesized model, with structural links freely estimated was conducted. The model fit was adequate: χ^2 [df = 408] = 1714.67 (Korean contribution to χ^2 = 991.43, U.S. sample contribution to χ^2 = 723.23), p < .001, RMSEA = .044 (90% CI (.042 - .046)), CFI = .989, and TLI = .988. Then, I ran a fully constrained model in which all paths are constrained to be equal across national groups. At this time, in addition to default constraints that accounted for partial scalar invariance, all structural paths across respective groups were constrained to be equal. The fit of the constrained model was adequate: χ^2 [df = 423] = 1791.62, p < .001, RMSEA = .044 (90% CI (.042 - .046)), CFI = .989, and TLI =

.988. However, the change in χ^2 between the freely estimated model and the constrained model was significant, $\Delta\ \chi^2$ [df = 15] = 77.05 suggesting that the strength of at least one of the regression coefficients was not comparable across the groups.

In order to identify which path coefficients are nonequivalent across all groups, I proceeded to conduct the iterative process of constraining and testing paths in the model and comparing these models to the baseline model, suggested by Little (1997). The equivalence testing proceeded in a stepwise fashion: the path producing the least amount of change in the χ^2 value was first constrained followed by the path that leads to the second smallest difference in $\chi^2$and so on until all fifteen paths had been constrained[9]. At each step, I compared the fit of each model (including constrained path/s) to the fit of the unconstrained model in which freely estimated structural paths until there was a significant change in the χ^2 in order to find the maximum number of equivalent paths in the structural model.

Table 4.10 presents the results of this stepwise analysis. First, I tested a model with a constrained the path from Math Self Concept to Math Intention (C_1) because this path produced the least amount of change in the χ^2 value compared to the unconstrained model. This procedure resulted in a $\Delta\ \chi^2$ [df = 1] = 0.36, p = .87.There was no change in the χ^2, suggesting that adding the extra constraint does not significantly reduce model fit. Next, I proceeded to constrain the path from Grade to Math Performance (C_2) because this path produced the second least amount of change in the χ^2 compared to the unconstrained model. The model still kept the path from Math Self Concept to Math Intention (C_3) constrained to be equal. This procedure resulted in a Δ

[9] To determine the order of path constraints, I first did 15 separate analyses in which one of the 15 hypothesized paths was constrained in a stepwise fashion, compared to the unconstrained model, and then examined how much the constraint of each path influence change in the chi-square value compared to the unconstrained model.

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χ^2 [*df* = 2] = 0.38, *p* = .82. Since this test was non-significant, I added the constrained path from Math Anxiety to Math Intention, keeping Math Self Concept → Math Intention and Grade→ Math Performance constrained to be equal across groups (C_4), again resulting in a non-significant change, $\Delta\chi^2$ [*df* = 3] = 1.42, *p* = .70. Until I added the constrained path coefficient from Math Self Concept to Math Performance (C_{11}), there was a nonsignificant change in χ^2 in the models of C_1 to C_{11}.

However, when I specified a constraint for the path from Math Performance to Math Intention (C_{12}), this lead to a significant change in χ^2 (DIFFTEST), $\Delta\chi^2$ [*df* = 12] = 15.66, *p* = .04. Then, when I left the path from Math Performance to Math Intention freely estimated and then specified a constraint for the path from Math Interest to Math Intention (C_{13}), these procedures also led to a significant change in χ^2: $\Delta\chi^2$ [*df* = 12] = 16.16, *p* = .03. When I specified a constraint for the path from Math Anxiety to Math Performance (C_{14}) and from Math Utility value to Math Performance (C_{15}), these procedures led to an additional significant decrease in χ^2 when compared with the unconstrained model: $\Delta\chi^2$ [*df* = 12] = 21.87 for C_{14} and 63.26 for C_{15}, $p < .001$.

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These results suggest that the strength of the relations among all of the hypothesized constructs were equivalent across the samples, except for four of the pathways that showed non-invariance across countries. The following strength of the relations were not equivalent across cultures: (a) from math interest to math intention, (b) from math performance to math intention, (c) from math utility value to math performance, and (d) from math anxiety to math performance. Results were similar for other plausible values. Additional information is provided in Appendix C to F.

Figure 4.3 presents the results of parameter estimates for multi-group comparison model with constraints on the 11 paths. For these constrained paths, one unstandardized path coefficient for the two countries is reported. It is important to remember that although the standardized values vary slightly across groups, the unstandardized values were constrained equal and are therefore identical for two groups. Results were similar for other plausible values. Additional information is provided in Appendix G and H.

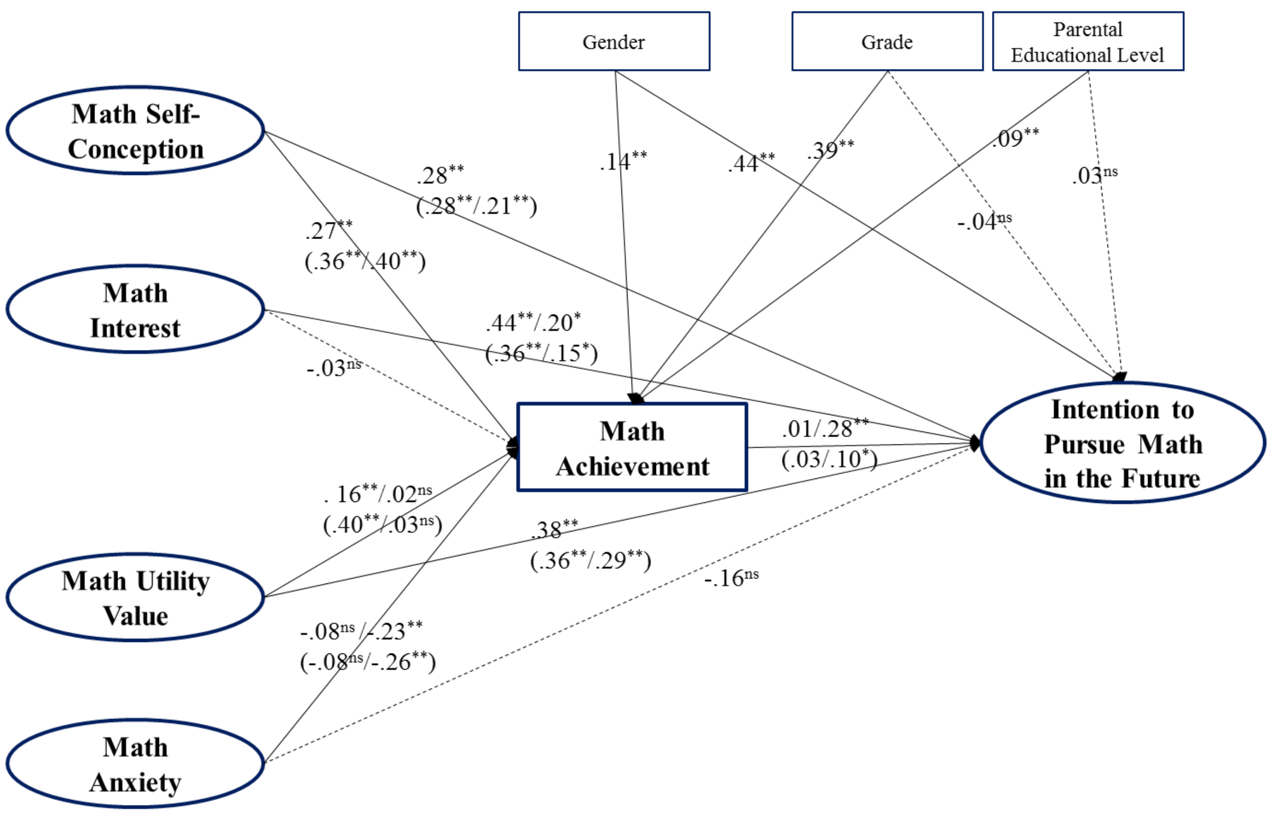

Figure 4.3. Unstandardized and Standardized Parameter Estimates for Multiple Group Structural Equation Model

Note. Math performance was measured by PV1. In parentheses, the first value is for Korean and the second value is for U.S. sample. Correlations between four motivation factors are not shown in this figure for the sake of simplicity; Dotted line indicates nonsignificance of the path coefficient.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

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Table 4.10

Results of Equivalence Test of the Structural Model across Samples

Model	χ^2	*df*	RMSEA	CFI	TLI	$\Delta\chi^2$	Δ *df*	p-value
Unconstrained model	1714.67	408	.044(.042- .046)	.989	.988			
C_1: Math Self Concept → Math Intention	1715.18	409	.044(.042- .046)	.989	.988	0.36	1	.87
C_2: Grade → Math Performance	1715.21	410	.044(.042- .046)	.989	.988	0.38	2	.82
C_3: Math Anxiety → Math Intention	1715.28	411	.044(.042- .046)	.989	.988	1.42	3	.70
C_4: Math Interest → Math Performance	1716.09	412	.044(.042- .046)	.989	.988	2.76	4	.60
C_5: Parental education → Math Performance	1717.98	413	.044(.042- .046)	.989	.988	2.91	5	.71
C_6: Parental education → Math Intention	1718.00	414	.044(.042- .046)	.989	.988	2.95	6	.81
C_7: Grade → Math Intention	1718.74	415	.043(.041- .045)	.989	.988	3.07	7	.88
C_8: Math Utility Value → Math Intention	1718.95	416	.043(.041- .045)	.989	.988	3.98	8	.61
C_9: Gender → Math Performance	1719.10	417	.043(.041- .045)	.989	.988	4.03	9	.59
C_{10}: Gender → Math Intention	1720.78	418	.043(.041- .045)	.989	.988	5.51	10	.70
C_{11}: Math Self Concept → Math Performance	1726.96	419	.043(.041- .045)	.989	.988	12.29	11	.10
C_{12}: Math Performance → Math Intention	1730.39	420	.043(.041- .045)	.989	.988	15.66	12	$.04^{*}$
C_{13}: Math Interest Value → Math Intention	1730.88	420	.043(.041- .045)	.989	.988	16.16	12	$.03^{*}$
C_{14}: Math Anxiety → Math Performance	1736.84	420	.043(.041- .045)	.989	.988	21.87	12	$.00^{***}$
C_{15}: Math Utility value → Math Performance	1777.39	420	.043(.041- .045)	.989	.988	63.26	12	$.00^{***}$
All paths constrained	1791.62	423	.044(.042- .046)	.989	.988	77.05	15	$.00^{***}$

Note. C_n indicates the model which includes the following constrained path. Math performance was measured by PV1. $\Delta\chi^2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Summary of structural invariance test results. The strength of the relations among all of the hypothesized constructs was equivalent across the samples, except for four pathways that showed noninvariance across countries: (a) from math interest to math intention, (b) from math performance to math intention, (c) from math utility value to math performance, and (d) from math anxiety to math performance. The nonequivalence identified for those four regression coefficients suggests that the relations among those constructs are possibly moderated by the sociocultural factors within each sample.

Summary of Results

Here, I present a summary of the hypotheses and whether each hypothesis was supported or not by the findings of this study.

Hypothesis 1. I hypothesized that that the measurement model would fit the data satisfactorily for both the Korean and U.S. samples. The results supported this hypothesis.

Hypothesis 2. I hypothesized that the constructs of math self-concept, math interest, math utility, and math anxiety were equivalent across U.S. and Korea. The result partially supported this hypothesis; a configural invariance was fully supported but a metric invariance and a scalar invariance was partially supported.

Hypothesis 3. I hypothesized that compared to the Korean sample, the U.S. sample would show higher level of math self-concept (Hypothesis 3.1), lower level of math interest (Hypothesis 3.2), lower level of math utility value (Hypothesis 3.3), and lower level of math anxiety (Hypothesis 3.4). The results partially supported these hypotheses; Hypothesis 3.1 and 3.4 were supported, however, Hypothesis 3.2 and 3.3 were not supported.

Hypothesis 4. I hypothesized that that the structural model would fit the data satisfactorily for both the Korean and U.S. samples. The result supported this hypothesis.

Hypothesis 5. I hypothesized that there are direct relations between each of four motivational constructs and math intention for both the U.S. and Korean samples (Hypotheses 5.1-5.4). The result partially supported these hypotheses; math self-concept (Hypotheses 5.1), math interest (Hypothesis 5.2), and math utility (Hypothesis 5.3) were directly related with math intention for both the U.S. and Korean samples.

Hypothesis 6. I hypothesized that current math performance mediates the relations between each of four motivational constructs and math intention for both the U.S. and Korean students (Hypotheses 6.1-6.4). The result partially supported these hypotheses. For the U.S. sample, math self-concept (Hypothesis 6.1), math utility (Hypothesis 6.3), and math anxiety (Hypothesis 6.4) were indirectly related to math intention via math performance. For the Korean sample, there was no indirect effect of math performance.

Hypothesis 7. I hypothesized that the strength of some associations between constructs in the expectancy-value model varies across U.S. and Korean samples.The results partially supported these hypotheses. Only four pathways were non invariant across U.S. and Korean samples: (a) from math interest to math intention, (b) from math performance to math intention, (c) from math utility value to math performance, and (d) from math anxiety to math performance.

CHAPTER 5: DISCUSSION

Informed by expectancy-value theory (Eccles et al., 1983), this dissertation examined the relations between math-related motivational beliefs and intentions to pursue math among Korean and U.S. adolescents. In this chapter, a summary of major findings is provided. Next, the importance of revisiting Eccles's expectancy-value theory, implications of measurement invariance testing in cross-cultural studies, and the paradoxical relation between motivation and math achievement are discussed in order to offer additional information on how the current results build upon prior studies in the literature. Lastly, implications of the study's results for future research and practice, limitations of the study, and a brief conclusion are presented.

Bringing Culture into the Conversation

Incorporating culture into educational research is important as it allows for a better understanding of adolescents' achievement motivation and academic choices. Adolescents are formally and informally socialized to a country's cultural values (i.e., conditions or characteristics that a society considers important) by everyday exposure to cultural customs and practices. These values shape individuals' priorities, attitudes, and ultimately their behaviors and beliefs, including their academic motivation (Schwartz & Ros, 1995). However, the perspective of viewing achievement-related beliefs as culturally embedded constructs has received relatively little consideration in the field of educational psychology (Elliott & Bempechat, 2002; Wigfield et al., 2004). Further, little is known about the utility of the expectancy-value model of academic choice for explaining variations in academic outcomes in non-Western populations, especially for East Asian students who tend to excel in tests of mathematics and science. That is to say, the functional effects of expectancy belief and task value constructs, which are emphasized in the expectancy-value model, have not been widely tested cross-culturally. By investigating cultural similarities and differences in the strength and/or presence of relations among motivational belief constructs (i.e., math self-concept, math interest, math utility value, and math anxiety), math performance, and intention to pursue math in the future using 15-year-old American and Korean adolescents, this dissertation adds to the body of evidence that supports the generalizability of the model across cultures.

Summary of Major Findings

Several important findings emerged from the study. First, there were significant mean-level differences in math-related motivation variables between U.S. and Korean students. Second, the mediating role of current math performance in explaining the relations between math-related motivational constructs and intention to pursue math in the future only existed for the U.S. sample. Third, there were cross-national similarities and differences in the direct pathways between motivational belief constructs and math intention, between motivation belief constructs and math achievement, and between math achievement and math intention. These findings will be discussed further in the sections that follow.

Mean Difference in Motivational Beliefs

MACS procedures were used to assess cross-national differences in motivational constructs included in the Eccles and colleague’s (1983) expectancy-value theory, which guided the current study. These variables included math self-concept, math anxiety, math interest, and math utility value. The results indicated that there were statistically significant differences among the mean levels of motivational variables between the U.S. and Korean sample.

Math self-concept. As hypothesized, U.S. students reported higher levels of math self-concept compared with their Korean counterparts. These findings confirm earlier cross-national studies. For example, Lee (2009) analyzed data from PISA 2003 and reported that U.S. adolescents were ranked 1st in math self-concept rating among 41 participating countries. In contrast, Korea was ranked 40th in math self-concept. Focusing primarily on self-concept of math ability, four other cross-national studies have reported lower values for East Asian countries, including Korea and Japan, when compared to Western countries, especially the U.S. (Marsh & Hau, 2004; Shen & Pedulla, 2000; Shen & Tam, 2008; Wilkins, 2004).

There are several possible explanations for these results. Regarding self-concept of ability, these cross-national differences may be due to cultural values. Compared to European Americans who are more likely to be motivationally oriented towards self-enhancement, East Asian students generally underestimate their abilities and display a tendency for self-criticism on their ability, which is culturally adaptive (Kitayama, Markus, Matsumoto & Norasakkunkit, 1997; Holloway, 1988). Under collectivistic cultures, which emphasize modesty of behaviors and enhancement of important others compared to the self, East Asian adolescents are discouraged from presenting and boasting their accomplishments and abilities to others (Markus & Kitayama, 1991).

Although not empirically investigated, these cross-national differences in math self-concept may also reflect differences in schooling experiences. Korean students feel more societal pressure to achieve academically and higher levels of parental involvement in school work. Also, they have to complete a greater number of normative school evaluations than U.S. students (Ho et al., 2000; Lee, 2009). The Korean educational environment may prevent students from having the opportunity to take ownership of their learning process, which can lead to discouragement when thinking about their academic abilities. According to self-determination motivation research on U.S. samples, this lack of perceived control can undermine a student's sense of ability (Deci & Ryan, 1987). Thus, a more controlling school environment may lead to the lower mean-level of math self-concept for Korean adolescents.

Math anxiety. Consistent with the hypotheses guiding the current study, U.S. students also reported lower levels of math-related anxiety than did Korean students. This finding is consistent with Lee (2009), who reported that U.S. adolescents ranked higher than Korean adolescents in math anxiety (18^{th} for the U.S. sample and 7^{th} for the Korean sample). Randel, Stevenson, and Witruk (2000) also indicated that Japanese students outperform German students in math, however, feel more negative emotion about math.

There are two possible explanations for this cross-national difference in math anxiety. Based on the findings consistently showing a strong negative relation between self-ratings of competence and anxiety (Fennema & Sherman, 1977; Frenzel, Pekrun & Goetz, 2007; Pajares & Miller, 1994; Meece et al., 1990), Korean students' low self-concepts of math ability may be a source of high levels of self-reported math anxiety. A low self-concept in math signifies that an individual is ill-equipped to handle demands of stressful situations involving math, thus leading to increased math anxiety (Ahmed, Minnaert, Kuyper, & van der Werf, 2012; Bandura, 1997). Meece et al.'s (1990) empirical study of young adolescents found that self-concept of ability measured at Grade 7 predicted math anxiety at Grade 9. Results of the current study support these patterns. As a group, Korean adolescents' lower ratings of math ability are related to high levels of math anxiety, whereas U.S. adolescents' higher math self-concept is strongly associated with low self-reported math anxiety.

These cross-national differences in math anxiety may also reflect differences in schooling experiences and parental expectation. As discussed earlier, East Asian students feel more societal pressure to achieve academically. In particular, during the middle-to-high-school transition, many Korean adolescents experience strong pressure regarding academic success and a heightened sense of competition to prepare to apply to top universities (Kim & Byun, 2014). Highly competitive educational environments can lower Korean youth's self-concepts of ability and heighten their anxiety ratings. In addition, Korean adolescents may display higher levels of fear of failure, perhaps as a response to higher parental expectations. In general, East Asian mothers show higher academic expectations for their children compared to mothers in the U.S. (Eaton & Dembo, 1997; Mau, 1997). Even for cases in which East Asian mothers rate their children lower in academic ability compared to U.S. parents, they maintain high expectations for school success (Stevenson et al., 1990). The burden to meet parents' high expectations often creates tremendous pressure on Korean students to achieve, leading to negative emotional reactions to the math such as math anxiety.

Math interest and math utility value. The mean differences in the U.S. and Korean adolescents' self-reports of math-related values were unexpected. For example, Henderson, Mark, and Kim (1999) compared math-related interest for children in Grades 2 through 5 from Korea, Japan, and the United States and found that students from Asian countries demonstrated higher levels of interest in academic areas (e.g., words, numbers, ideas, etc.) than children from the U.S. When compared to U.S. adolescents, prior studies suggested that East Asian youth may place more value on usefulness of mathematics for their futures (Stevenson et al., 1990; Sun, Ding, & Chen, 2013). Results from the current study were not consistent with this pattern. In contrast to proposed hypotheses, the results showed that the U.S. sample reported higher levels of math interest and math utility value when compared to the Korean sample.

Although not empirically investigated, cross-national differences in math value may reflect differences in parental expectations and schooling experiences. According to self-determination theory, controlling educational climates undermine youth's intrinsic motivation (Niemiec & Ryan, 2009). For example, studies showed that evaluative pressures in the classroom undermine students' interest and the value students attach to math for both U.S. students (Grolnick & Ryan, 1987) and Japanese students (Kage & Namiki, 1990). Because East Asian high schools are characterized as more controlling, competitive, and academically demanding when compared to U.S. schools, negative schooling experiences that Korean students may often face can lower their self-reported math interest and math utility value. Moreover, East Asian youth are likely to feel more controlled by their parents (Kao, 1995; Kim & Wong, 2002). East Asian parents have high demands and expectations exerted on children in order to maintain a high level of performance. Thus, they are more involved in their children' academic performance by checking over their children's work, assigning additional work, and structuring and monitoring their time (Huntsinger & Jose, 2009). These perceived academic pressures and a lack of perceived control may lead lower math interest and math utility value for Korean adolescents.

From a theoretical perspective, the lower levels of math interest and math utility reported by Korean adolescents versus U.S. adolescents are, in part, explained by prior studies investigating the relations between ability belief and value beliefs. Contemporary expectancy-value studies have consistently reported positive correlations between math self-concept and math-related values (e.g., Eccles & Wigfield, 1995; Gottfried, 1985; Wang & Degol, 2013). Children who are not highly skilled in an area are less likely to place value on it as a way to preserve a sense of competence (Eccles et al., 1993; Harter, 1986). In addition, due to people's tendency toward wishful thinking, adolescents are likely to overestimate their probability of success on activities they value highly (Eccles & Wigfield, 1995; Feather, 1982). Meece and colleagues (1990) empirically showed a strong relation between students' self-concept and value beliefs in mathematics. A recent study by Wang and Degol (2013) also indicated strong positive relations between self-concept and value beliefs. Students who reported higher mean levels of self-concept also reported higher mean levels of task value at the same time. Empirical results from the current study support to this theoretical explanation. Positive relations between measures of math self-concepts and math-related values appeared for both the U.S. and Korean samples.

Direct and Indirect Effect of Motivation on Math Intention

The main purpose of the study was to examine the relations between math-related motivational beliefs, math performance, and intention to pursue math among Korean and U.S. adolescents. I tested a conceptual model that features a series of direct and indirect effects of motivational belief constructs on intention to pursue math in the future using a multiple group analysis. At the outset of the study, I hypothesized that there would be direct relations between (a) math self-concept and math intention, (b) math interest and math intention, (c) math utility value and math intention, and (d) math anxiety and math intention for both the Korean and U.S. sample. In addition, I hypothesized that math performance would mediate these four relations for both the Korean and U.S. sample.

Study hypotheses were partially supported. Math performance emerged as a mediator between math-related motivational beliefs and math intention for U.S. students only. There were cross-national similarities and differences in the pathways hypothesized in the structural model:

(a) between four motivational beliefs and math intention (direct effect), (b) between four motivational beliefs and math performance (indirect effect), and (c) between math performance and math intention (indirect effect). Each part of the structural model is discussed separately below.

Direct paths between motivation beliefs and math intention. The current study adds to prior findings by examining direct relations from different motivational constructs to math intention. As predicted, there were direct pathways between (a) math self-concept and math intention, (b) math interest and math intention, and (c) math utility value and math intention for both the Korean and U.S samples. Previous findings consistently support expectancies and values as strong predictors of academic-related choices (Eccles et al., 1983). For instance, youths' intentions to enroll in elective math and science courses were associated with their interests and beliefs about the importance of these domains (Atwater, Wiggins, & Gardner, 1995; Meece et al., 1990).

However, contrary to research hypotheses, there was no direct relation between math anxiety and math intention for either the Korean or U.S. samples. This particular finding replicates the Meece et al.'s (1990) study with respect to the relative influences of performance expectancies, value perceptions, and math anxiety on course enrollment intentions in math. In that study, researchers found that math anxiety did not have a significant direct effect on course enrollment intentions. Rather, course enrollment decisions were directly predicted by ability and value beliefs. Students' rating of anxiety indirectly predicted course enrollment intentions through a negative relation to competency-related beliefs, which, in turn, showed a strong relation to course enrollment plans (see Meece et al., 1990). The current study using the Korean and U.S. adolescent samples replicated this prior study. There were significant direct relations from math-related ability and value contructs to future math enrollment intentions. In keeping with Meece et al. (1990), math-related anxiety functioned to lower to future math enrollment intention, when variables such as self-concept, perceived usefulness, and interest were considered together.

Direct path between motivation and math performance. With regard to the indirect effect of four motivation belief constructs on math intention, my hypotheses included that there would be direct relations from different motivational constructs to math performance for both the Korean and U.S. sample.

Results indicated that direct the path between math self-concept and math performance was significantly positive for both the Korean and U.S. samples. The positive relation between math self-concept and math achievement is supported by previous findings showing that ability beliefs have strong direct effects on performance (e.g., Denissen et al., 2007; Durik et al., 2006; Marsh et al., 2005; Meece et al., 1990). These positive relations were also replicated with East Asian samples (e.g., Shen & Pedulla, 2000; Shen & Tam, 2008). A recent study by Marsh and Hau (2004) validated the generalizability of a pattern of positive relations between math self-concept and math achievement across 26 countries using PISA 2000 data. My findings add to the literature in establishing a positive link between math self-concept and math performance across adolescent samples from Korea and the U.S.

With regard to value constructs and math performance, math interest was not related to math performance in either the Korean or the U.S. samples. However, there were different patterns of relations for the utility value construct. Math utility value was positively associated with math performance for the Korean sample, but no relation was found for the U.S. sample. In contrast to this set of findings, math anxiety was negatively associated with math performance for the U.S. sample, but no significant relation appeared for the Korean sample. Each of cross-nationally variant paths is discussed with plausible explanations in the subsequent sections.

Math utility value and math performance. The path between math utility value and math performance was only significant for the Korean sample. Regardless of lower mean levels of math utility value for the Korean than U.S.samples, their math performance may show a stronger relation to levels of their math utility values. As Wigfield and colleagues (2004) argued, data based on Asian samples display positive relations between subjective task values and math achievement, irrespective of measures of mathematics achievement. With the self-determination framework, utility value is similar to a form of *extrinsic motivation*, because when doing an activity out of utility value, the activity is considered to be "a means to an end rather than an end in itself" (Wigfield, Tonks, & Klauda, 2009, p. 58). Previous empirical intrinsic and extrinsic motivation studies reported that the relation between extrinsic forms of motivation and academic achievement is stronger in collectivist countries than in individualistic countries (Chiu & Chow, 2010; Deci & Ryan, 2002; Moneta & Siu, 2002). This finding adds to the knowledge regarding the influential role of the sense of utility of a task, in explaining math achievement for East Asian students.

Math anxiety and math performance. The path coefficient for the relation between math anxiety and math performance was significantly negative for the U.S. sample and there was no similar relation for the Korean sample. Previous studies using U.S. samples have shown that anxiety negatively relates to students' achievement (see Hembree, 1988). However, little is known about the generalizability of the negative relation between math anxiety and achievement, particularly in Asian nations where students report higher achievement in mathematics compared to their U.S. counterparts (Beaton et al., 1996; Stevenson et al., 1990). Lee (2009) showed for

Asian countries, such as Hong Kong, Japan, and Korea, the correlations between students' math scores and math anxiety were relatively lower compared to correlations for students in Eastern European countries and the U.S. Thus, math anxiety may not be a powerful predictor when other motivation variables such as self-concept and task values, especially utility value, are controlled for Korean students. This finding adds to the knowledge regarding the cross-national difference in the role of math anxiety in explaining mathperformance.

Direct path between math performance and math intention. With regard to the indirect effect of four motivation belief constructs on math intention, my hypotheses proposed a direct relation from math performance to math intention for both the Korean and U.S. samples. One surprising finding was the differences in relations for the two samples. The relation between math achievement and math intention was statistically significant and positive for the U.S. sample, but it was not statistically significant for the Korean sample.

My results showed that there was a positive relation between math performance and math intention for the U.S. sample. When U.S. students demonstrated higher levels of performance on concurrent measures of mathematics achievement, they were more likely to report intentions to pursue math in the future. This finding emerged with variance related to motivation beliefs included in the model. This finding partially supports prior research showing that academic performance influences educational plans or actural college enrollment (Carpenter & Fleishman, 1987; Eccles, Vida, & Barber, 2004; Simpkins, Davis-Kean, & Eccles, 2006). By contrast, for Korean students, a high math performance level was not significantly associated with a high level of pursuing math in the future. Unlike the positive role of current math performance level for the U.S. sample, objective measures (i.e., test scores) were not predictive of intentions to pursue mathematics for the Korean sample.

There are several possible reasons for the conflicting findings between the Korean and U.S. samples. Instead of current math performance level, Korean students may be more likely to rely upon social contextual factors when determining whether to continue taking advanced math courses or apply additional effort towards math in the future. Within collectivist cultures, there are shared *cultural expectations* regarding the desirability of high achievement in certain fields of study (Markus & Kitayama, 1991), and these cultural expectations may shape activity choices to a greater degree than objective measures of achievement. In Korean cultures, for example, young people are expected to attain high levels of achievement, especially in math and science. Thus, as observed in the current study, value beliefs, rather than performance levels, predicted Korean students' intentions to continue taking mathematics.

In addition, peers and parents in Asian cultures play a significant role in academic choices. Compared to the U.S. samples, Asian students use the performance of peers to judge their capabilities to perform a similar task. The observation of peers' performances conveys to students that they, too, are capable of accomplishing the task at hand, if they choose similar tasks (Markus & Kitayama, 1991). Most importantly, parental influence is critical for Asian students' determination of academic choices. Even though students may have a low achievement level, and rate themselves as having low academic ability for achieving success in an academic task, they are willing to choose the task when their parents hold high academic expectations for them or place a high value on the task (Stevenson et al., 1990). Cultural and parental expectations are critical components of the expectancy-value theory (Wigfield et al., 2004), and these sources of influence on Korean students' math-related activity choices need further examination in future studies.

Different Strength of Relations across Cultural Groups

The last purpose of the study was to examine whether the strengths of the relations were invariant across U.S. and Korean cultural groups. The multigroup analysis confirmed that some of the relations did vary across cultural groups. There were cross-national variances in four path coefficients (a) from math interest to math intention, (b) from math performance to math intention, (c) from math utility value to math performance, and (d) from math anxiety to math performance. Except for these four relations, the strengths of the rest of relations (discussed in the previous sections) were equivalent across samples. That is, the two samples from different cultural backgrounds exhibited structurally invariant patterns of these associations.

My study showed that four relations were structurally different across the Korean and U.S. samples. As already discussed in the earlier section, the relations (b) between math anxiety and math performance and (d) between math performance and math intention and were significant for only the U.S. sample. On the other hand, the relation between (c) math utility value and math performance was significant for only the Korean sample. As I explained, the nonequivalence may be moderated by the sociocultural factors such as the role of significant others, schooling experience, and cultural norms within each sample.

Regarding nonequivalence of the relation (a) between math interest and math intention across groups, the relation was significant and positive for both samples, however, the strengths of the relations were stronger for the Korean sample compared to the U.S. counterpart. Regardless of the lower mean-levels of math interest for the Korean sample, their math intention may depend more on the level of their math interest as well as perceived utility, acting as more powerful predictors than percpetions of math abilities. Although not empirically investigated, the cross-national differences in the relation may reflect differences in the degree of the influence of value constructs. Under the collectivistic cultural contexts in which self-presentation on competence is discouraged and modesty is emphasized, value constructs may show stronger relation to activities compared to ability constructs (Markus & Kitayama, 1991). As previously explained, achievement in mathematics and science is highly valued in East Asian cultures. For adolescents who internalized these cultural expectations, highly valued achievement-related tasks are perceived as the most desirable choice for them. This possibility should be tested directly because very few empirical studies examining relations between task value and academic-related intention using East Asian samples (Wigfield et al., 2004).

Revisiting Eccles's Expectancy-Value Theory

Wigfield, Tonks, and Eccles (2004) argued that the expectancy-value model is "particularly well suited for a cultural analysis of motivation and activity choices" (p. 169) because the original Eccles et al. model was designed to explain a sociocultural phenomenon. Through a number of previous studies, this model has explained how gender, school-level factors, and cultural stereotypes about different subject areas and occupations influence students' expectancies and values. However, expectancy-value researchers have not paid attention on the influences of the broader cultural milieu in which individuals grow up. The study is one of the first of its kind to examine whether Eccles et al.'s expectancy-value model can be extended to diverse students, especially those from non-Western cultures.

Many, but not all, of the relations proposed in the hypothesized expectancy-value model (*Figure 4.2*, see p. 100) can be applied to Korean students, who often belong to collectivist cultures. As empirically shown, the majority of the paths in the expectancy-value model are equivalent across cultures. For both Korean and U.S. samples, there are direct paths from ability beliefs (e.g., math self-concept) and task values (e.g., math interest and math utility value) to math intention. In addition, there is a direct relation between ability beliefs (e.g., math self-concept) and math achievement for both samples. The results add to the literature in establishing the generalizability of the relations across cultures. The relations were initially examined using a sample of American students and later replicated across samples from Western cultures (e.g., Australia or Canada). Results of the current study indicate a possible extension of the expectancy-value model to non-western cultural contexts.

However, the relative predictive power of some of the motivational constructs used to explain adolescents' math achievement and math intention vary across cultures. Four cross-national differences in relations among constructs emerged in the study. A high level of math utility value was associated with high math performance, but only for Korean students. On the other hand, for U.S. students only, low levels of math anxiety were related to high math performance and, in turn, high levels of math performance were related to high math intention. There was a significant relation between math interest and math intention for both Korean and U.S. students; however, math interest was more strongly associated with math intention for Korean than U.S. youth. These cross-national differences in the relations may reflect social, educational, and cultural factors of the society. As discussed earlier, value constructs as well as other sociocultural factors, such as parental expectation or a controlling school environment, are more strongly associated with Korean adolescents' activity choice or performance, rather than self-concepts of ability. Cross-cultural differences in perceptions of parental expectations and the schooling environment need to be examined empirically in future studies.

In summary, many of the basic linkages proposed in the expectancy-value model have received some preliminary support from prior cross-cultural studies as well as this current study. However, there are also variations in the strengths of these relations in different cultures, even if the relations are present across groups. To date, many motivation studies, including expectancy-value studies, have focused on proximal contexts (e.g., classroom context and parents' or peers' influence) and have tended to neglect the larger, or more distal, cultural context (King & McInerney, 2014). Thus, more work is needed to establish the utility of the expectancy-value model of academic choice for understanding adolescents' motivation and academic choices in different cultural contexts.

Implications of Measurement Invariance for Understanding Cultural Variations

Findings from the current study confirmed the importance of evaluating measurement invariance in culturally heterogeneous samples. Little (1997) described four important aspects of measurement equivalence: (a) the constructs are generalizable across sociocultural contexts that are tested; (b) there is a minimal degree of bias and error on measurement across contexts; (c) the constructs underlying measurement characteristic are not differentially affected by sociocultural differences; and (d) sociocultural difference in the construct's mean, variances, and covariance relations can be assessed quantitatively.

Results of measurement invariance testing revealed that the motivation belief scale displayed a *partial measurement invariance*. The evidence of noninvariance for the scale suggests that adolescents from different cultural groups interpreted, conceptualized, and/or simply might be responding to some items differently. The invariance testing of PISA motivational items showed a *partial scalar invariance* that included one non-invariance factor loading across groups. The unstandardized factor loading on one item (i.e., "I get nervous doing math") was substantially lower for Korean students than for U.S. students, which suggests that the item contributes less to Korean students' latent math anxiety score than it does for the U.S. students' score. One plausible explanation for this result is that the item "I get nervous doing math" showed a relatively high correlation with the other math anxiety item "I get tense when I have to math" for the Korean sample. Eight thresholds were also noninvariant across groups. Examination of these threshold patterns across groups revealed that thresholds for U.S. students were lower than those of Korean students. These results suggest that U.S. students may have a propensity to respond more strongly to certain items (e.g., *strongly agree* instead of *agree*; Sass, 2011). It is also possible that members of different cultural groups interpreted response option labels differently when responding to these items (Chen, 2007).

The results add to a growing body of evidence suggesting that the importance of invariance testing in cross-cultural studies cannot be underestimated. Even the cognitive measurement scales of PISA, which have been well-developed and validated by experts from different countries, showed a partial non-invariance on some items. In most prior comparative studies, adolescents simply had to respond to investigator-generated items, most often created by Western researchers and then translated (Bempechat et al., 2002). The findings from previous studies are limited and inconclusive because observed differences in the constructs might result from a differential functioning of an instrument, rather than reflecting genuine differences (Byrne et al., 1989). Thus, measurement invariance should be considered and tested in cross-cultural studies.

Paradoxical Phenomena Related to Motivation

Several cross-national comparison studies have consistently documented a puzzling finding regarding the mean-levels of self-concept and academic achievement across nations (e.g., Lee, 2009; Shen & Pedulla, 2000; Shen & Tam, 2008). Students who report high self-beliefs usually have lower performance (e.g., East Asian countries) and vice versa (e.g., U.S.). Among 41 countries in the PISA study, for countries where the mean level of students' math achievement scores is high, these countries also tend to be ranked at the bottom in terms of mean levels of self-concept (Lee, 2009). The current study provides further evidence of this paradoxical phenomenon. In the U.S., where students' math achievement is relatively low on national assessments, national averages indicate that U.S. students tend to feel more interested in math, show stronger appreciation for math attainment, and report lower math anxiety. Conversely, in Korea, where students' math achievement is relatively high national averages, they tend to report lower math interest and math utility value, and higher levels of math anxiety.

However, the currtent study provides insights into this paradoxical phenomenon when relations in the expectancy-value model are examined from a cross-cultural perspective. Although Korean students, as a group, rated math interest and value as low, the relations from these value constructs to math achievement and choices were stronger for Korean than for U.S. students. High levels of math utility value were associated with high math achievement, only for Korean samples. In addition, there was a stronger association between math interest and math intention for Korean youth. Thus, the role of value constructs in the structural model of this study is helpful for understanding paradoxical patterns that arise between self-concepts of ability and academic achievement across U.S. and Asian countries. For Asian countries, math-related value beliefs (i.e., interest and utility values) can be critical predictors of math performance and intentions to continue taking mathematics, regardless of self-concept of ability. If cultural norms emphasize the value on mathematics and science achievement, then students in these countries may perform well and continue their study in those domains regardless of perceived capabilities. Thus, the data provide prelimary evidence that cultural norms and expectatations, rather than personal beliefs about ability, play a significant role in the educational attainment of East Asian adolescents.

Contributions of Current Study

This study offers several contributions. First, there is a lack of empirical studies examining whether Eccles et al.'s expectancy-value model can be extended to diverse students, especially those from non-Western cultures. This study begins to fill this gap. Specifically, the findings from this study support Wigfield et al.'s (2004) argument that because Eccles et al.'s original model was designed to explain a sociocultural phenomenon, the model would be well suited for a cross-cultural analysis of motivation and academic choices. The results showed that many of the structural relations in the expectancy-value model can be applied to a Korean sample. Second, an empirical investigation of the potential relations among these variables adds to the extant body of literature in educational psychology. The findings provide an insight about the role of motivational beliefs in predicting math-related choices by examining whether there is still a unique association between motivational beliefs and intention to pursue math in the future, even after controlling for the mediating effect of actual math performance level. Third, the current findings indicate the importance of measurement invariance as a prerequisite for comparing scores across cross-cultural groups. Lastly, the most practical contribution of the study is that it informs teachers, educators, and policymakers of the sociocultural forces that underlie the relative predictive power of motivational constructs for explaining variations in math achievement and math-related choices. Understanding differentiated effects of motivation can aid in the discovery of potential targets for future intervention as well as in the creation of a culturally responsive learning environment. The study suggests that, although it is of major concern for international educational professionals and reformer to improve students' math and science achievement levels, simply transplanting educational practices from high achieving countries, such as Korea, Japan, and China, to low achieving ones will not result in similar performance levels. With regard to achievement motivation, youth are strongly influenced by the underlying values of their cultural context. Thus, without thoughtful consideration of the cultural foundation upon which motivation models are used to explain educational outcomes, limited evidence will emerge to improve youth's academic performance. Broader cultural models of academic motivation and educational attainment are needed (Elloitt & Bempechat, 2002; Wigfield et al., 2004).

Future Directions

The findings from this investigation have the potential to stimulate future research in educational psychology and research using cross-cultural samples of students. As mentioned, students' task values have received scant consideration compared with that of students' expectancy and ability beliefs in cross-cultural work (Wigfield & Eccles, 2000). As such, a number of critical areas remain open for investigation. A starting point may be to replicate the mean-difference of task value components (i.e., interest, utility value, importance, and cost), as well as the examination of the strengths of the relation between different task value and adolescents academic choices, with diverse samples from different nations. A longitudinal examination of the reciprocal relations between competence beliefs, subjective values, math achievement, and math intention is also needed to allow for a better understanding of the processes that shape adolescents' academic choices.

In addition, the current hypothesized model needs to be revised or extended in the future studies by considering additional variables. For example, in order to examine the roles of math-related motivation constructs in predicting math performance, the variable of *prior math achievement level* should be included in the model. In addition, recent cross-cultural research has emphasized individual variations within cultures. Individuals who identify within a particular culture do not always behave in similar ways or hold the same beliefs as their peers because daily experiences in contexts such as family, school, and community differ across individuals. Without considering personal characteristics, individual behaviors and psychological characteristics cannot be explained by the culture *per se* (Zusho et al., 1995). Thus, various individual -, parent -, and school - related variables must be considered in future studies.

From a methodological standpoint, future research efforts could undertake a person-centered approach to studying motivational processes on adolescents' academic-related choices. Expectancy and value components of motivation do not always work in perfect harmony (Denissen et al., 2007). Previous research has identified subgroups of students low in self-efficacy and high in task value (Pintrich, 1989) or vice versa (Roeser, Strobel, & Quihuis, 2002). Thus, in order to provide better picture of the process of adolescents' motivation, a person-centered approach is needed to identify motivation profiles within individual and then compare the patterns across individuals and cultures.

Lastly, data from only two countries were analyzed in the current study. Future studies should seek to establish the generalizability of motivational processes in other nations. Results from the current study highlight the role of cultural differences (i.e., individualism in the United States and collectivism in East Asian countries) which play in the development of adolescents' motivation. Future studies should incorporate data from other Asian countries such as Japan or China, in order to determine if the results hold across other Asian cultural groups. Despite many East Asian countries being historically embedded in collectivist cultures, each of these nations has its own political, economic, and educational context. Thus, in order to validate the results of the Korean sample with other East Asian students, more studies are needed.

Limitations of the Study

First, although I used a sophisticated procedure to analyze the data and examine my hypotheses, the PISA 2012 data is cross-sectional in nature, and thus, directions of any possible causal relations cannot be ascertained with these data. For example, the results supported the finding that math achievement partially mediated the effect of math-related motivation on intention to pursue math in the future for U.S. sample. This result indicates that math-related motivation predicted students' math achievement. Nevertheless, it is equally plausible to suggest that math achievement predicts students' math-related motivation. Longitudinal data is required to formulate more exact predictions concerning the causality of the implicated processes.

Next, as this study is a secondary analysis, the data were limited by the assessments employed by PISA 2012 and the response selections provided. Additional and more specialized measurements to assess outcomes would contribute to the generalizability of the effects of motivational beliefs found in the current study. For instance, I proposed that the measures of math intention consist of only two available items. The measurement of math intention was focused upon participants' future efforts to pursue math in the future, such as "taking additional classes after school finishes" or "studying harder in math class than is required." Additional measurements to assess intention related to adolescents' educational (e.g., major in the college) or career choices (e.g., planning a math-related career) are needed to present a more comprehensive picture of adolescents' math-related intention and its relation to motivation and achievement. In addition, because PISA math achievement assessment is more focused on one's overall cognitive competencies on math, GPA or other math performance assessment focused on mastery of school curriculum may be needed to examine whether the result can be replicated when a measurement of achievement varies. Existing literature implemented GPA or teachers' report as a measurement of one's achievement level, and these determinations are perceived as being more obvious sources of comparison between students (Hansford & Hattie, 1982).

Third, because my research was focused on *between-country difference*s in motivation and its relation to math achievement and math intention, I assumed a relative *homogeneity within a nation* and substantial *heterogeneity between nations* in my dissertation study (Feinstein & Peck, 2008). In this dissertation, in order to reduce the impact of within-country variation for explaining between-country differences of motivation and math-related outcomes, great care was taken to select variables that were deemed important based on the literature, and as such, I included grade level, gender, and parental educational level as control variables in the analysis. However, it is important to note that this still leaves out a majority of teacher, student, and school variables that may contribute to the unexplained variance.

Fourth, there are several limitations related to the analytic techniques used. For example, as discussed, there are no standard criteria for evaluating practical fit cutoff for measurement invariance testing when WLSMV is utilized (Sass, 2011). Moreover, the current study assumed that a *partial scalar invariance* is an adequate condition for establishing (a) a justification for the cross-group comparisons of factor means, and (b) multi-group structural equation analysis (Bryne, 2012; Chen, 2007). However, there has been still some controversy about whether a *full measurement invariance* (i.e., a *strong factorial invariance*) is required for substantive analyses or not, as discussed earlier in the result section (see p. 95). Thus, I note that mean-level differences in motivational beliefs across nations which were examined in the current dissertation should be interpreted with caution.

Conclusions

Grounded in the Eccles et al.'s expectancy-value model of academic choice, this study explored the relations between motivational beliefs and intention to pursue math in the future, with a particular focus on the mediating role of current math performance. The present research also examined cross-national cultural similarities and differences in these relations using sample of 15-year-old U.S. and Korean adolescents who participated in PISA 2012. Findings from this study provided evidence that expectancy beliefs (i.e., math self-concept) and value beliefs (i.e., math interest and math utility value) are directly associated with intention to pursue math in the future for Korean and U.S. student samples. The mediating role of current math performance in explaining these relations was only documented for the U.S. sample, and not for the Korean sample. Math self-concept was associated with math performance for both samples, however, there was a positive association between math utility and math performance only for the Korean sample. And for the U.S. sample only, there was a positive relation between math performance and math intention as well as a negative relation between math anxiety and math performance. This study adds to motivation research by addressing the unique influence of various motivation constructs in explaining adolescents' academic choice and providing insights into the accumulation of knowledge in the expectancy-value model of achievement motivation cross-nationally.

APPENDIX A. STANDARDIZED DIRECT, INDIRECT, AND TOTAL EFFECTS FOR MATH INTENTION USING PV2 TO PV5

	Math Intention Korea		
	Direct	Indirect	Total
Predictor			
MSC	$0.14^{**}/0.14^{*}/0.13^{*}/0.14^{*}/$	0.02/0.02/0.02/0.02	$0.16^{**}/0.16^{**}/0.16^{**}/0.16^{**}$
MI	$0.31^{***}/0.31^{***}/0.31^{***}/0.31^{***}$	0.00/0.00/-0.01/-0.01	$0.30^{***}/0.30^{***}/0.30^{***}/0.30^{***}$
MUV	$0.29^{***}/0.28^{***}/0.28^{***}/0.28^{***}$	0.01/0.02/0.02/0.02	$0.30^{***}/0.30^{***}/0.30^{***}/0.30^{***}$
MA	-0.06/-0.06/-0.06/-0.06	0.00/0.00/0.00/0.00	-0.06/-0.06/-0.06/-0.06

	Math Intention U.S.		
	Direct	Indirect	Total
Predictor			
MSC	$0.26^{***}/0.26^{**}/0.25^{**}/0.24^{**}$	$0.01^{*}/0.01^{*}/0.02^{*}/0.02^{*}$	$0.27^{**}/0.27^{**}/0.27^{**}/0.27^{**}$
MI	$0.12^{*}/0.12^{*}/0.13^{*}/0.13^{*}$	-0.01/-0.01/-0.01/-0.02	$0.11/0.11/0.11^{*}/0.10^{*}$
MUV	$0.31^{***}/0.31^{***}/0.30^{***}/0.30^{***}$	0.00/0.00/0.00/0.01	$0.31^{***}/0.31^{***}/0.31^{***}/0.31^{***}$
MA	-0.07/-0.07/-0.06/-0.06	$-0.02^{*}/-0.02^{*}/-0.03^{*}/-0.03^{*}$	-0.09/-0.09/-0.09/-0.09

Note. MSC= math self-concept; MIV= math interest value; MUV= math utility value; MA= math anxiety; MI= intention to pursue math in the future. The result was from a multiple SEM.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

APPENDIX B. STANDARDIZED DIRECT PATHWAY ESTIMATES USING PV2 TO PV5

Structural Path	Korean sample standardized	U.S sample standardized
Math Self Concept → Math Intention	.14 (.06)**/14 (.07)*/ 14 (.07)*/.14 (.06)**	.26 (.09)**/ 26 (.09)**/ 25 (.08)**/ .26 (.09)**/
Math Interest → Math Intention	.31 (.07)***/31 (.07)***/31 (.07)***/ 31 (.07)***	.12 (.07)*/.12 (.07)*/.13 (.07)*/.12 (.07)*
Math Utility Value → Math Intention	.29 (.05)***/28 (.05)***/28 (.05)***/ 28 (.05)***	.31 (.05)***/ .31 (.05)***/.30(.05)***/. 30(.05)***
Math Anxiety → Math Intention	-.06 (.04) /-.06 (.04) /-.06 (.04)/ -.06 (.04)	-.07(.06) /-.07(.06) /-.06(.06)/ -.06(.06)
Math Self Concept → Math Performance	.33 (.06)***/.39 (.06)***/.40 (.06)***/. 39(.06)***	.21 (.06)***/.23 (.06)***/.25 (.06)***/.23 (.06)***
Math Interest → Math Performance	-.06(.12) /-.09(.07)/-.09(.07)/-.09(.07)	-.05 (.05) /-.06 (.05)/-.06 (.05) /-.06 (.05)
Math Utility Value → Math Performance	.25 (.06)***/.24 (.04)***/.25 (.04)***/	.06 (.04) /.07 (.04)/.06(.03)/. 06(.03)
Math Anxiety → Math Performance	-.02 (.05)/-.01 (.04)/-.01 (.04)/ -.01 (.04)	-.40 (.05)***/ -.38 (.05)***/ -.36 (.05)***/-.38(.05)***
Math Performance → Math Intention	.05 (.03) /.06 (.03)/ .06 (.03)/ .06 (.03)	.10 (.04)*/ .09 (.04)*/.08(04) */.08(04) *
Gender → Math Intention	.16 (.03)***/.16 (.03)***/ .15 (.03)***/.15 (.03)***	.13 (.03)***/ .13 (.03)***/.13(.03) ***/.13(.03) ***
Grade → Math Intention	.01 (.04) /01 (.03) /01 (.03)/01(.04)/	-.00 (.04) /-.00 (.04) /-.00 (.04)/-.01(.04)
Parental Education → Math Intention	.04 (.04) /04 (.04)/ 04 (.04) / 04 (.04)	.05 (.04) /06 (.04)/.05 (.04)/.05 (.04)
Gender → Math Performance	.09(.03)*/.09(.03)**/.09(.03)**/.09(.03)**	.07 (.03)*/ .07 (.03)*/.05 (.04) */.05 (.04) *
Grade → Math Performance	.11 (.04)**/.10 (.04)**/.10 (.04)**/ .11 (.04)**	.27 (.03)***/ 27 (.03)***/ 25 (.03)***/ 27 (.03)***
Parental Education → Math Performance	.23 (.03)***/22 (.03)***/22 (.03)***/ 23 (.03)***	.25 (.03)***/ 26 (.03)***/ 27 (.03)***/ 26 (.03)***

Note. The result was from a multiple SEM.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

APPENDIX C. RESULTS OF EQUIVALENCE TEST OF THE STRUCTURAL MODEL USING PV2

Model	$\chi2$	*df*	RMSEA	CFI	TLI	$\Delta\ \chi2$	Δ *df*	p-value
Unconstrained model	1710.88	408	.044(.042- .046)	.989	.987			
C_1: Math Self Concept → Math Intention	1711.42	409	.044(.042- .046)	.989	.987	0.24	1	.68
C_2: Grade → Math Performance	1711.43	410	.044(.042- .046)	.989	.987	0.26	2	.88
C_3: Math Anxiety → Math Intention	1711.85	411	.044(.042- .046)	.989	.988	0.97	3	.81
C_4: Math Interest → Math Performance	1712.07	412	.044(.042- .046)	.989	.988	1.19	4	.52
C_5: Parental education → Math Performance	1712.54	413	.044(.042- .046)	.989	.988	1.55	5	.62
C_6: Parental education → Math Intention	1713.21	414	.043(.041- .045)	.989	.988	2.40	6	.81
C_7: Grade → Math Intention	1714.65	415	.043(.041- .045)	.989	.988	3.40	7	.85
C_8: Math Utility Value → Math Intention	1714.76	416	.043(.041- .045)	.989	.988	3.78	8	.60
C_9: Gender → Math Performance	1715.33.	417	.043(.041- .045)	.989	.988	4.44	9	.61
C_{10}: Gender → Math Intention	1716.61	418	.043(.041- .045)	.989	.988	5.73	10	.70
C_{11}: Math Self Concept → Math Performance	1726.68	419	.043(.041- .045)	.989	.988	15.39	11	.11
C_{12}: Math Performance → Math Intention	1727.66	420	.043(.041- .045)	.989	.988	16.75	12	$.03^{*}$
C_{13}: Math Interest Value → Math Intention	1729.46	420	.043(.041- .045)	.989	.988	18.68	12	$.03^{*}$
C_{14}: Math Anxiety → Math Performance	1733.26	420	.043(.041- .045)	.989	.988	22.52	12	$.02^{**}$
C_{15}: Math Utility value → Math Performance	1775.85	420	.043(.041- .045)	.989	.988	64.88	12	$.00^{***}$
All paths constrained	1788.25	423	.044(.042- .046)	.989	.988	77.33	15	$.00^{***}$

Note. C_n indicates the model which includes the following constrained path. Math performance was measured by PV2. $\Delta\ \chi2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

APPENDIX D. RESULTS OF EQUIVALENCE TEST OF THE STRUCTURAL MODEL USING PV3

Model	$\chi 2$	*df*	RMSEA	CFI	TLI	$\Delta\ \chi 2$	Δ *df*	p-value
Unconstrained model	1708.99	408	.044(.042- .046)	.989	.987			
C_1: Math Self Concept → Math Intention	1709.26	409	.044(.042- .046)	.989	.987	0.24	1	.68
C_2: Grade → Math Performance	1709.40	410	.044(.042- .046)	.989	.989	0.27	2	.83
C_3: Math Anxiety → Math Intention	1709.96	411	.044(.042- .046)	.989	.988	0.90	3	.83
C_4: Math Interest → Math Performance	1711.50	412	.044(.042- .046)	.989	.988	2.51	4	.64
C_5: Parental education → Math Performance	1711.78	413	.044(.042- .046)	.989	.988	2.60	5	.77
C_6: Parental education → Math Intention	1711.79	414	.043(.041- .045)	.989	.988	2.63	6	.85
C_7: Grade → Math Intention	1711.83	415	.043(.041- .045)	.989	.988	2.71	7	.85
C_8: Math Utility Value → Math Intention	1712.45	416	.043(.041- .045)	.989	.988	3.46	8	.81
C_9: Gender → Math Performance	1712.69	417	.043(.041- .045)	.989	.988	3.63	9	.83
C_{10}: Gender → Math Intention	1714.26	418	.043(.041- .045)	.989	.988	5.23	10	.82
C_{11}: Math Self Concept → Math Performance	1726.64	419	.043(.041- .045)	.989	.988	17.50	11	.09
C_{12}: Math Performance → Math Intention	1727.76	420	.043(.041- .045)	.989	.988	18.90	12	$.04^{*}$
C_{13}: Math Interest Value → Math Intention	1728.62	420	.043(.041- .045)	.989	.988	19.63	12	$.03^{*}$
C_{14}: Math Anxiety → Math Performance	1731.70	420	.043(.041- .045)	.989	.988	22.79	12	$.02^{**}$
C_{15}: Math Utility value → Math Performance	1765.44	420	.043(.041- .045)	.989	.988	56.00	12	$.00^{***}$
All paths constrained	1774.17	423	.043(.041- .045)	.989	.988	65.92	15	$.00^{***}$

Note. C_n indicates the model which includes the following constrained path. Math performance was measured by PV3. $\Delta\ \chi 2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

APPENDIX E. RESULTS OF EQUIVALENCE TEST OF THE STRUCTURAL MODEL USING PV4

Model	$\chi 2$	*df*	RMSEA	CFI	TLI	$\Delta\ \chi 2$	Δ *df*	p-value
Unconstrained model	1707.89	408	.044(.042- .046)	.989	.987			
C_1: Math Self Concept → Math Intention	1707.95	409	.044(.042- .046)	.989	.987	0.22	1	.64
C_2: Grade → Math Performance	1708.17	410	.044(.042- .046)	.989	.989	0.28	2	.86
C_3: Math Anxiety→ Math Intention	1708.97	411	.044(.042- .046)	.989	.988	1.08	3	.78
C_4: Math Interest → Math Performance	1710.17	412	.044(.042- .046)	.989	.988	2.39	4	.66
C_5: Parental education → Math Performance	1710.21	413	.044(.042- .046)	.989	.988	2.32	5	.80
C_6: Parental education → Math Intention	1710.31	414	.043(.041- .045)	.989	.988	2.40	6	.88
C_7: Grade → Math Intention	1710.39	415	.043(.041- .045)	.989	.988	2.50	7	.91
C_8: Math Utility Value → Math Intention	1710.94	416	.043(.041- .045)	.989	.988	3.07	8	.90
C_9: Gender → Math Performance	1712.32	417	.043(.041- .045)	.989	.988	4.50	9	.85
C_{10}: Gender → Math Intention	1713.71	418	.043(.041- .045)	.989	.988	5.81	10	.80
C_{11}: Math Self Concept → Math Performance	1723.77	419	.043(.041- .045)	.989	.988	15.95	11	.08
C_{12}: Math achievement → Math Intention	1725.81	420	.043(.041- .045)	.989	.988	17.45	12	$.04^{*}$
C_{13}: Math Interest Value → Math Intention	1725.91	420	.043(.041- .045)	.989	.988	18.01	12	$.03^{*}$
C_{14}: Math Anxiety → Math Performance	1729.82	420	.043(.041- .045)	.989	.988	22.08	12	$.02^{**}$
C_{15}: Math Utility value → Math Performance	1768.37	420	.043(.041- .045)	.989	.988	61.07	12	$.00^{***}$
All paths constrained	1780.28	423	.043(.041- .045)	.989	.988	72.93	15	$.00^{***}$

Note. C_n indicates the model which includes the following constrained path. Math performance was measured by PV4. $\Delta\chi 2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

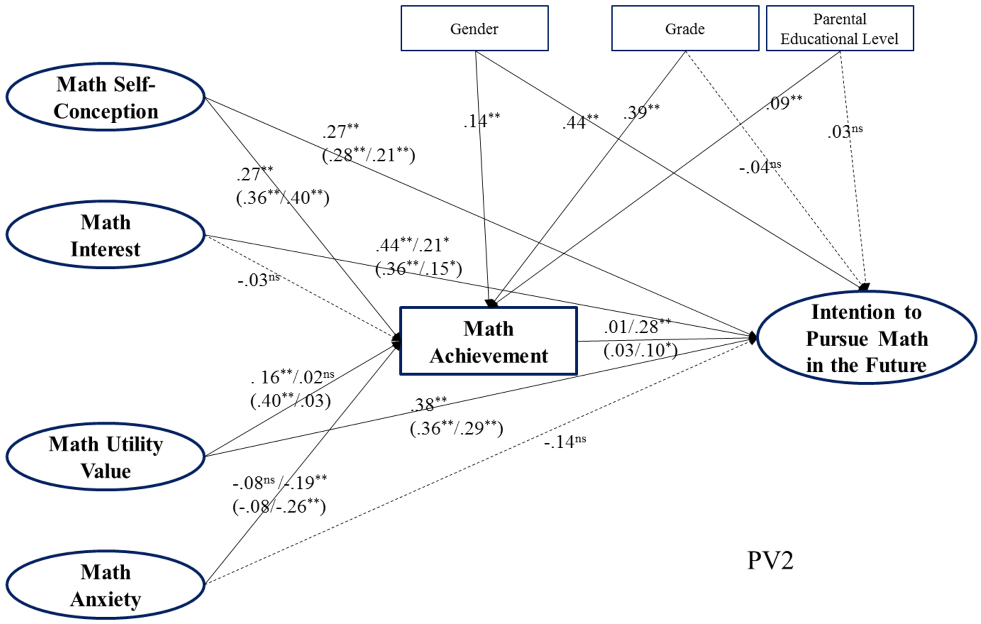
APPENDIX F. RESULTS OF EQUIVALENCE TEST OF THE STRUCTURAL MODEL USING PV5

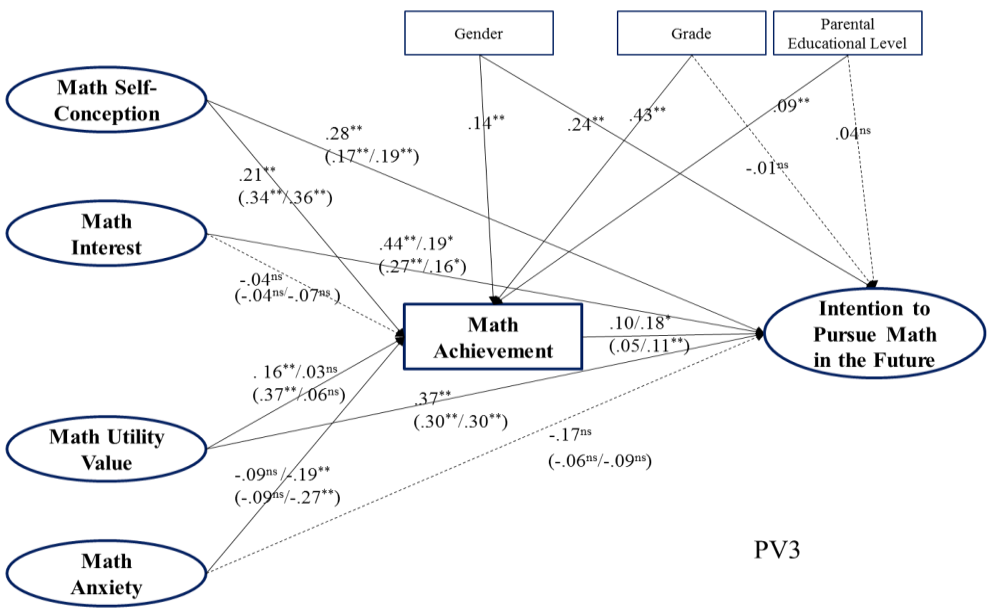
Model	$\chi 2$	*df*	RMSEA	CFI	TLI	$\Delta\ \chi 2$	Δ *df*	p-value
Unconstrained model	1708.49	408	.044(.042- .046)	.989	.987			
C_1: Math Self Concept → Math Intention	1708.66	409	.044(.042- .046)	.989	.987	0.27	1	.60
C_2: Grade → Math Performance	1708.72	410	.044(.042- .046)	.989	.987	0.35	2	.84
C_3: Math Anxiety → Math Intention	1709.69	411	.044(.042- .046)	.989	.988	1.13	3	.77
C_4: Math Interest → Math Performance	1710.61	412	.044(.042- .046)	.989	.988	2.12	4	.64
C_5: Parental education → Math Performance	1710.58	413	.044(.042- .046)	.989	.988	2.50	5	.77
C_6: Parental education → Math Intention	1711.01	414	.043(.041- .045)	.989	.988	2.58	6	.87
C_7: Grade → Math Intention	1711.09	415	.043(.041- .045)	.989	.988	2.60	7	.89
C_8: Math Utility Value → Math Intention	1711.44	416	.043(.041- .045)	.989	.988	2.92	8	.90
C_9: Gender → Math Performance	1712.11	417	.043(.041- .045)	.989	.988	3.55	9	.91
C_{10}: Gender → Math Intention	1713.59	418	.043(.041- .045)	.989	.988	5.10	10	.88
C_{11}: Math Self Concept → Math Performance	1719.50	419	.043(.041- .045)	.989	.988	11.42	11	.30
C_{12}: Math achievement → Math Intention	1727.70	420	.043(.041- .045)	.989	.988	19.16	12	$.04^{*}$
C_{13}: Math Interest Value → Math Intention	1729.10	420	.043(.041- .045)	.989	.988	20.51	12	$.03^{*}$
C_{14}: Math Anxiety → Math Performance	1730.90	420	.043(.041- .045)	.989	.988	22.41	12	$.03^{**}$
C_{15}: Math Utility value → Math Performance	1764.52	420	.043(.041- .045)	.989	.988	56.06	12	$.00^{***}$
All paths constrained	1775.74	423	.043(.041- .045)	.989	.988	66.68	15	$.00^{***}$

Note. C_n indicates the model which includes the following constrained path. Math performance was measured by PV5. $\Delta\ \chi 2$ reports the difference in chi-square generated by the DIFFTEST option in M*plus*.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

APPENDIX G. UNSTANDARDIZED AND STANDARDIZED PARAMETER ESTIMATES FOR MULTIPLE GROUP SEM USING PV2 AND PV3

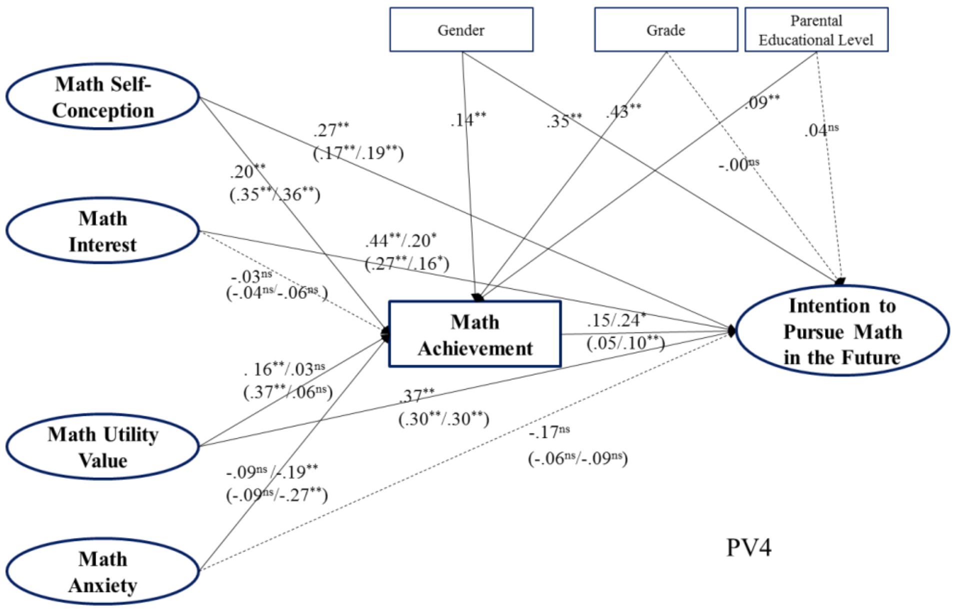


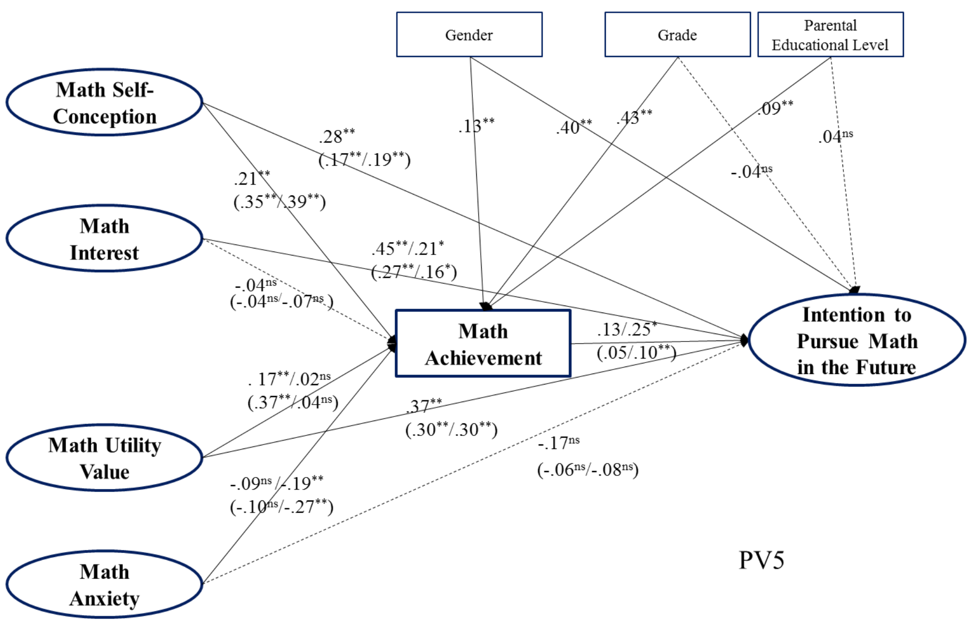


Note. Correlations between four motivation factors are not shown in this figure for the sake of simplicity. Dotted line indicates non-significance of the path coefficient.
$^{*}p < .05$ $\quad ^{**}p < .01$ $\quad ^{***}p < .001$

APPENDIX H. UNSTANDARDIZED AND STANDARDIZED PARAMETER ESTIMATES

FOR MULTIPLE GROUP SEM USING PV4 AND PV5





Note. Correlations between four motivation factors are not shown in this figure for the sake of simplicity. Dotted line indicates non-significance of the path coefficient.
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

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