An Investigation of the Role of Mathematical Attitudes in the Motivation of Teacher Grade Level Choice Using the Expectancy-Value Theory.

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Dedication

I want to give a heartfelt thank you to my brother Brandon. You are the bravest person I know. I will never forget all the lessons you taught me. At a young age, you taught me how to be courageous, independent, and the importance of standing up for myself. Thank you so much for everything you have ever done for me.

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Abstract

Background: Research has identified achievement motivation to be a predictor of career choice. Despite this, there is limited research investigating why pre-service teachers choose specific grade levels. An understanding of motivations to enter teaching may provide insight into teacher quality at different grade levels. Research has identified minorities and females as underrepresented in STEM fields. Additionally, minorities and female teachers are disproportionately overrepresented in lower grade levels. While previous studies have examined differences in gender and race/ethnicity representation in education, this study sought to investigate whether mathematical attitudes played a role in grade-level choice. **Purpose**: Drawing on Expectancy-Value Theory (Eccles, et al., 1983), this causal-comparative study investigated the role of various mathematical values in preservice teacher's grade level choice. **Methods**: The study utilized a 38-item survey to collect data from 353 preservice teachers enrolled in the University of Houston System, The University of Texas at Austin, and Texas A&M University. The survey gathered demographic information for participants, and measured indicators for Math Expectancy Values and Math Subjective Task Values. Survey questions were adopted from specific instruments, *The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale*, and *The Mathematics Value Inventory for General Education Students*. **Data Analysis**: Structure Equation Modeling was used to analyze associations between Mathematical Subjective Task Value and Math Expectancy in subsamples of preservice teachers of different grade level choice, gender, race/ethnicity, and groups who were obtaining a mathematics certification. **Results**: The results showed that the latent variable Mathematical Attribution of Expectancy was predicted by the latent variables for Math Self-Concept and Math Self Efficacy and were positively related to Mathematical Task Value for female preservice teachers. Models showed acceptable fit for samples of overall preservice teachers, all female preservice teachers, and all minority/not Asian female preservice teachers, all minority/not Asian preservice teachers. The models demonstrate overall teachers had positive mathematical beliefs. The results are inconclusive for teachers of different ethnicity and gender.

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Chapter 1

Introduction

Ever since the *Nation at Risk* report was released in 1983, educators have debated the issue of mediocrity and national competitiveness regarding the United States' education system (Fink & Inkelas, 2015). The *Nation at Risk* reported that American public school rigor was decreasing and high-school graduates were less competitive relative to both previous generations and against international students (Gardner et al., 1983). The Nation at Risk provided specific concerns regarding the growth and strength of math and science education in the United States (Kelley & Knowles, 2016). Since the Nation at Risk report, American students have demonostrated little to no growth in the area of mathematical readiness (Alton, 2019; Venneman et al., 2009). The National Center for Education Statistics reported that students aged 9 and 13 demonstrated minimal growth in mathematical readiness, 17 year olds have demonstrated non-significant growth (National Center for Education Statistics, 2013). Today, those statistics are largely unchanged. According to Herrera et al. (2017), nationwide growth in math proficiency increased less than 1%.

Many students graduating from high school are unprepared for STEM fields due to a lack of preparation for the rigors of college level mathematics (Long et al, 2009; Melguizo & Ngo, 2020; Park et al, 2021). A study from Long et al. (2009) that examined the relationship between taking rigorous courses and post-secondary performance found a significant difference between those students who took rigorous courses and their academic success in college and those who did not. The authors estimated that at least one-third of all graduating high school seniors were unprepared for college-level mathematics.

In addition to rigor, data indicate that some graduating seniors lack the prerequisites to enter the STEM pathway in college. The National Center of Education Statistics reports that only 24.9% of high school students have completed at least pre-calculus (Brown et al., 2018), and yet research suggests that students lacking preparation for calculus are at a disadvantage for STEM success as calculus is an essential course for STEM preparation (Ellis et al., 2016).

Currently, American universities are reporting underrepresentation of students in majors related to Science, Technology, Engineering, and Math (STEM) fields; within many STEM fields the students who do graduate with STEM degrees are mostly international students (Clotfelter, 2010; Zwetsloot et al., 2020). The specific reasons for the underrepresentation of students in STEM include a lack of academic persistence (Mau, 2016), a lack of representation of groups such as Hispanics, African-Americans and females, (Banerjee & Lamb, 2016), and a need for educational interventions such as teacher support, teacher training and clear standards, to improve math and science outcomes in primary and secondary education (Melguizo & Ngo, 2020; Tai et al., 2006; Webb et al., 2002).

In addition to academic preparedness, high school graduates with limited mathematical skills may face narrower career options than those graduates with stronger mathematical skills (Curry, 2017; Espino et al., 2017). A key reason for this likely is that mathematics is fundamental to Science, Technology, Engineering, and Math (STEM) career fields (Norris, 2012). STEM fields have the distinction of being one of the fastest growing sectors of the economy in the United States (Ali, 2020; Thomson, 2021). Indeed, between the years 2000 and 2010, the growth of STEM-related jobs reached a rate of three times of non-STEM related jobs (Smithsonian Science Education Center, 2018). STEM jobs in the United States are going unfulfilled at a rate of 2.4 million jobs a year (Smithsonian Science Education Center, 2018).

King et al. (2017) maintained that a mathematical education provides broader learning opportunities and transferable skills including the ability to communicate with experts and non-experts, working in teams, writing and ethical thought. With a decrease in manufacturing jobs, mathematics skills are increasing marketable in non-STEM trades such as middle-skill jobs (Burning Glass Technologies, 2017; Claymier, 2014). Specifically, mathematics-related skills are not only beneficial to improving opportunities to earn a higher income, but also Problem solving, critical thinking, communicating, and collaborating have been linked to quality STEM education (Gravemeijer et al., 2017). Finally, mathematics supports cognitive development and provides development of problem and decision-making skills (Ghazal, 2014).

The term minority is a race-/ethnicity-based label and reflects specific race/ethnicities of “blacks or African Americans, Hispancs, or Latinos, and American Indians or Alaska Natives” (Bhatti, 2021, p. 1). The challenge facing minorities who are at an educational disadvantage is that the current economic landscape shows the United States' labor market becoming a more polarizing labor force of higher paying, technically demanding jobs, and low paying non-skilled positions (Kalleberg, 2011; Kuller & Gallego, 2019). The consequence is that future social mobility will require proficiency in abstract, problem-solving, creative, and coordination tasks, skills found in mathematical disciplines (Acemoglu & Autor, 2011; Autor & Dorn, 2013). The combination of the narrow economic opportunities, the socioeconomic status of the family, and the lesser access to quality teaching provides may limit social mobility among minority groups. Indeed, minority representation is lacking in STEM subjects (Bhatti, 2021; Fisher et al, 2019). For example, in 2019 only less than three percent of African Americans had a science degree, and overall representations of minority groups in science careers are traditionally low with Africans American representing seven percent of science careers (National Science Foundation, 2019).

Math education also plays a prominent role in gender equality. Specifically, men are overrepresented in mathematical-based STEM careers (Cimpian et al., 2020). According to the Bureau of Labor Statistics (2018), females are under-represented in the professions of electrical and electrical engineers: 25.6%; mechanical engineers: 9.4%; chemists: 10.9%; and material scientists: 37.7%. Explanations for these differences include lower self-concept among women (Sax et al., 2015), attitudes about these subjects (Tekerek et al., 2011), decreased participation in academic subjects related to the fields (Hernandez et al., 2013; Jackson et al., 2013), and a shortage of female teachers in these subjects (Bottia et al., 2015). In contrast, fields in the humanities have an overrepresentation of females. The Bureau of Labor Statistics (2018) reported an overrepresentation of females in areas such as public relations: 72.8%; fundraising managers: 77.9%; human resource managers: 72%; medical and health services managers: 76.3%; meeting, convention, and event planners: 69.3%; and fundraisers: 69.3%.

The gender imbalance in STEM also may play an important role in women's achievement in the workplace. For example, STEM fields pay drastically more than the humanities, resulting in women, on average, making less than their male counterparts (Noonan, 2017; Sterling et al., 2020). In the discussion about a female wage gap, part of the explanation is at least partially due to career choice, and career attitudes. For example, Bensidoun and Trancart (2018) reported that 6.3% of the pay difference between men and women was due to differences in choices of careers and attitudes towards technical fields. Specific research on variations in the workplace has found characteristics associated gender differences in the workplace include differences in self-esteem, self-efficacy, and personality (Jin et al., 2009; Mueller & Dato-on, 2008; Wulff & Steitz, 1999). These factors are additionally associated with gender academic achievement gap (Di Giunta, et al., 2013).

Further evidence of mathematical education inequality for federally protected classes is a performance on the SAT (Akpotor & Egbule, 2020; Choi, 2018; Oliver, 2017). The SAT is a test taken by high school seniors, and most American universities base admission decisions in part on SAT performance

(Bastedo et al., 2019; Carnevale et al., 2019). Results from 2017 SAT scores indicated a difference among different racial and ethnic groups, with Asians on average scoring a 612 on the mathematics section; Whites scoring 553, Latinos scoring 487, and African Americans scoring 462 (Marini, et al., 2019). Indeed, recent research found that the most significant predictor of SAT scores is race, not social class (Geiser, 2015). The significance of SAT achievement is that according to Briggs (2001), the College Board (2012), and Scott et al. (2010), the SAT is considered at least partially a measure of student readiness and a prediction of academic success in college.

The United States has significant inequality in health, access to economic and social resources, and quality of life, and the unequal distribution of these resources and experiences are endured primarily by low-income individuals and families (Parker et al., 2012; Paula et al., 2012; von Rueden et al., 2006). Funding for public schools comes from local property taxes which contributes to a situation of unequal funding for high poverty and minority schools, reflecting the disparities in educational outcomes (Scholes, et al., 2017). The issues of funding leads to differences in teacher quality. Hanushek et al. (2004), Lankford et al. (2002), and Scafidi et al. (2007) all reported that many American teachers prefer to work in situations where the pay is higher, students are wealthier, and have higher achievement.

The primary factor influencing the effectiveness of a student's education at the school level is the quality of the teachers (Bhai & Horoi, 2019; Cardichon et al., 2020; Schumacher et al., 2015; Stronge & Hindman, 2003). An ineffective teacher can drastically influence the tragectory of a student's academic career (Fitchett & Heafner, 2018). According to Hill et al. (2005), in mathematics, the math preparedness of middle and secondary school students is dependent on the quality of instruction in elementary school. Primary school mathematics is the foundation of mathematical learning, with first through fourth grade identified as the most pivotal period for Quantitative Literacy (QLT) development (National Association for the Education of Young Children, 2010). QLT refers to application, problem-solving, and mathematical reasoning (Young-Loveridge & Peters, 2005).

Thus, mastery of mathematics in primary school is a necessity for students to keep pace with peers as they progress toward high school graduation. Students who fall behind their peers develop at a slower rate and tend to remain behind (Aunola et al., 2004; Polo, 2020; Rose, 2020, Sanders & Rivers, 1996. Some students reach high school so far behind that schools are forced to track students in a secondary school based on ability (Burris & Garrity, 2008).

Differences in mathematical achievement for both females and minorities appear in early grades and widens as students age (Fryer & Levitt, 2004; Lockwood, 2007; Reardon & Galindo, 2009; Thompson & O'Quinn, 2001). The differences in mathematical achievement is attributed by some to differences in ability (Baye & Monseur, 2016), with boys benefiting more from quality schools (Autor et al., 2016). Some also attribute differences in math achievement to perceived teacher quality perceptions (Hochweber & Vieluf 2018).

In conclusion, currently schools struggle with placing quality teachers in key positions (Wiggan, 2021; Peyton et al., 2021). One at need position is mathematics and other teachnical subjects necessary for higher paying jobs in society (Kalleberg, 2011, Kurer, 2019). Teacher quality is a primary concern for student readiness, and ultimate success in an academic domain (Ansari et al., 2020; Hattie, 2009). Mathematical educational quality in the United States is a concern for secondary achievement, career choices in STEM and is a strong factor in representation in STEM fields (Ashirbayev et al. 2018; Dontha, 2018). Based on the data in the literature on math achievement in K-12, the quality of math teachers at the primary levels is a contributor to this issue.

Background to the Problem

The United States is currently experiencing a widespread teacher shortage, with schools having trouble filing positions with qualified teachers (Garcia & Weiss, 2019; Katz, 2018). Many factors contribute to the shortage of teachers. Research from Hilton (2017) identified perceptions of the profession, including a lack of respect, stress, and low pay as dominant factors.

The shortage of teachers has been especially impactful in specific core content areas such as mathematics and science (Carber-Thomas, 2017; Shein, 2019; Wiggan et al., 2021). The shortage influences practices for recruiting and retaining quality teachers (Berry, 2017; Eck, 2019, Wiggans, 2021). The indicators for teacher quality generally include certification, relevant training, and experience (Garcia & Weiss, 2019; Harris & Sass, 2011; Pedaste, 2019). Due to teacher shortages, school districts are hiring underqualified teachers (Donitsa-

Schmidt et al. 2020; Ivie, 2021). It was reported that one-third of all California mathematics teachers in 2014-15 were either interns, permits or waivers (Darling-Hammond et al., 2016). The teacher shortage places undue pressure on teachers (Steiner-Khamsi & Teleshaliyev, 2020), with working conditions being a defining factor for teacher attrition (Geiger & Pivovarova, 2018). Teacher attrition particularly hits poorer schools--which serve predominately students of color--leaving the schools with unfilled positions or pressure to keep underperforming teachers (French, 2018; Garcia & Weiss, 2019).

Concerns about teacher quality have led to policies to ensure students are receiving high quality instruction (Akiba & LeTendre, 2017; Goldhaber et al., 2019). Certification standards ensure teachers are qualified to teach in the classroom and end of year assessments are in place to ensure students are meeting certain benchmarks (Bystritskaya et al., 2020; Johnson & Morris, 2021; Terada, 2021). The initial NCLB outlines evaluation guidelines for end of year assessment in each grade level which were later adopted in the Every Students Succeeds Act of 2015 (Act, 2015; Epstein, 2004; Steinberg & Quinn, 2017). Current law does not require tests for kindergarten, first, and second grades (Act, 2015; Hart et al., 2015; Epstein, 2004; Steinberg & Quinn, 2017). Title A, part A National Final Regulations (NFR) in ESSA requires regular state assessments in specific subjects, including mathematics (Hart et al., 2015; Steinberg & Quinn, 2017). However, there is no state assessment in early primary (United States Department of Education, 2016). School districts did not have access to test information on individual students until fourth grade when the EOC exam scores returned (Hart et al., 2015; Steinberg & Quinn, 2017). Standardized test scores are one piece of information districts use to make a judgment of teacher effectiveness (Guarino et al., 2013).

Statement of the Problem

In the United States, differences in general student achievement begins at primary school (Bowman, 2018; Goodall, 2017; Olszewski-Kubilius & Corwith, 2018). Although there are many factors involved in explaining low achievement at the primary level, including poverty, lower academic expectations, safety, and curriculum rigor, the most significant factor at the school level is the teacher (Garcia & Weiss, 2019; Hattie, 2009). Teaching at the primary level is important for mathematical learning throughout a student's career (Lindberg et al., 2010). Data reported in the 2019 National Assessment of Educational Progress (NAEP), a project of the United States Department of Education, suggested differences in math student achievement begins at the primary level (Ji et al., 2021). For example, 40% of fourth-graders, 33% of eighth graders and 25% of 12th graders scored at least proficient in mathematics, suggesting that a mathematics gap appeared in elementary school and grew as students moved through the system (Desilver, 2017). The challenge of any performance gap is that students will require intensive intervention to catch up to the rest of their peers.

The need to understand the role of mathematics in teacher motivation is necessary to address the trend of underqualified teachers, especially in areas of mathematics. Differences in teacher motivation to enter different levels may explain a significant factor of educational quality at different levels and provide a specific focus for intervention. The quality of math teachers is related to preparation and attitudes towards mathematics, especially regarding self-efficacy (Perera & John, 2020; Xu & Qi, 2019). This research investigated the motivation of preservice teachers to choose different grade levels and considered how mathematical beliefs and attitudes influence motivations to enter different grade levels as an explanation to the perceived mathematical achievement gap.

Finally, there is no research related to motivational factors in teacher grade-level choices. There also is not extensive research that considers the role of mathematics in grade-level choices excluding one dissertation within the past seven years (Pearson, 2012). Previous research has applied the Expectancy Value Theory (EVT) to explain career motivations (Ball et al., 2017; Ball et al., 2019; Wu & Fan, 2017). EVT is well grounded as a motivational theory (Moos & Marroquin, 2010), in education EVT is a powerful framework to understand how students perceive their individual competency and how they value their ability in an academic context (Eccles, 1983, 1987; Eccles, et al., 1989, Lauermann et al., 2017; Wigfiled, 1994; Wigield & Eccles, 1992, 2000). EVT has been applied to predict motivation to enter STEM careers (Chen et al, 2013; Lykkegaard & Ulriksen 2016; Steegh, et al. 2021; Wang & Degol, 2013). Researchers applied EVT to research of preservice teachers to understand factors to enter the teaching profession (Richardson & Watt, 2014). EVT has not previously been used to describe the motives for grade-level choice in education, and this research attempts to demonstrate the use of EVT to explain teacher motivation in grade-level choice.

Purpose of the Study

This study seeks to test the effect of pre-service teachers' beliefs about mathematics on their choice of grade level. Using EVT (Eccles, et al., 1983), I posit that pre-service teachers' beliefs about mathematics help them decide which grade level they want to teach, such that pre-service teachers with more negative beliefs about math are more likely to choose to teach at the elementary level. I also intend on discovering whether gender and ethnicity plays any role in the preservice grade-level choices.

Research Questions

In this cross-sectional study, the researcher answered the following questions:

1. Is the hypothesized second-order factor model of mathematical task values and attribution of expectancy tenable for pre-service teachers?
2. To what extent did pre-service teachers' motivational beliefs about mathematics, measured by Mathematical Attribution of Expectancy and Mathematical Task Values, affect the grade level they chose to teach in?
3. Is the hypothesized factor structure valid for different groups of preservice teachers (e.g. caucuasion/white, minority/Not-asian, male, female)?

Research Hypotheses

$H1_1$: Items 1-6 are indicators for the first-order latent variables Mathematical Self-Efficacy; items 7-10 are indicators for the first-order latent variables Mathematical Self-Concept; items 11-17 are indicators of the first-order latent indicator Interest; questions 18- 24 are indicators of the first-order latent variable General Utility; items 25-31 are indicators for the first-order latent variable Need for High Achievement; items 32-38 are indicators of the first-order latent variable Personal Cost.

$H1_2$: Mathematical Self-Efficacy has a positive effect on Mathematical Attribution of Expectancy; Mathematical Self-Concept has a positive effect on Mathematical Attribution of Expectancy, Interest has a positive effect on Mathematical Task Values; General Utility has a positive effect on Mathematical Task Values; Need for High Achievement has a positive effect on Mathematical Task Values; Personal Cost has a positive effect on Mathematical Task Values.

$H1_3$: The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical Attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical Task Values are dependent on gender, such that the effect of Mathematical Attribution of Expectancy and Mathematical Task Value is stronger when the gender is female.

$H1_4$: The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical Attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical Task Values are dependent on ethnicity, such that the effect of Mathematical Attribution of Expectancy and Mathematical Task Value is stronger when the ethnicity is Caucasian/white.

Theoretical Foundations

Expectancy Value Theory (EVT) is used to conceptualize how individuals' motivations help explain their decisions and outcomes (Eccles et al., 1983). Eccles and her colleagues first utilized the expectancy-value Theory in education in the 1980s to explain achievement related choices to academic behaviors. The Expectancy-Value Theory states that achievement-related choices are a combination of the expectancy of success in engaging in an activity and the subjective task value in the specific domain (Eccles et al., 1983).

As a theoretical framework, researchers applied the Expectancy Value theory successfully been used to show planned regulation (Ajzen, 2020; Magidson et al., 2014), emotional regulation (Tamir et al., 2015), and even explain achievement-related behavior (Barron & Hulleman, 2015). The theory suggests that the combination of subjective task values and math expectancy values leads towards motivation to do a task. Researchers have successfully applied the Expectancy Value Theory to both career and education choices (Ball et al., 2017; Ball et al., 2019; Wu & Fan, 2017). For example, the Expectancy Value model has been used to predict student career choices in mathematical fields (Ball et al., 2016; Lauermann et al., 2017; Meece et al., 1990). Additionally, expectancy and task-value beliefs demonstrated a substantial role in adult career choices in areas such as mathematics (Boll et al., 2017; Song et al., 2017). Specifically, three factors consistently identified in research to predict choices of mathematics courses and careers that utilize math skills, including math teaching are views of ability, expected future success, the individuals' subjective valuing of math (Wang et al., 2013; Wang, 2012).

Significance of the Study

Previous research is deficient in investigating the motivation of teacher's choice in grades of K-12. This was the first study to apply EVT to describe the motives for grade level choice in education. This study sought to address the motivation of grade choice level of preservice teachers by applying EVT to address whether individual beliefs of ability in the domain of mathematics explained preservice teacher's choice of grade level. This study attempts to answer the important question about how teachers make the choice of grade level and the extent that mathematical self-efficacy contributes to grade level choice.

This research can be used to inform academic specialists, policymakers, practitioners, community leaders, and professionals not specializing in research about the quality of math educators to consider for policies regarding certification, hiring, and review. Additionally, this research attempts to provide an insight into the quality of math education in the lower grades. Furthermore, this research attempts to provide information to inform researchers to explain the differences in mathematical achievement internationally and pinpoint specific issues in early-primary training and instruction.

Limitations

The limitations of this research are standard of using survey data, such as non-response, the accuracy of subject respondents, and validity due to closed answers. In the study itself, the questionnaire is self-reported, and the responses were limited to the engagement of participants. Further research could address the issue of closed answers through the implementation of a mixed-method study to improve internal validity.

This study investigated the desires of the grade level of preservice teachers and not the actual placement of teachers. As such, this study did not collect data on the actual placement of teachers. The inability to track the placement of preservice teachers is a limitation on the external validity of this research. Specifically, the conclusions made in this study may not accurately represent actual grade level placement and may not apply to the actual population of teachers serving at the reported levels.

Furthermore, the generalization of the study is that the difference in grade-choice level may be at least partially due to general perceptions of academic rigor, including, but not limited to mathematics. An individual's actual mathematical ability may be a significant role in grade level choices. This study does not test the actual mathematical skill of the preservice teachers.

Delimitations

One of the more critical assumptions of the study is the similarity of a sample to the population. The sampling occurred in Houston, Texas, and Austin, Texas. According to Capps et al. (2015) and Troyer (2019), Houston, Texas is the most diverse metropolitan area in the United States. Austin, Texas was selected for the population of the study because it is home to the University of Texas Austin (UT Austin) and Texas A&M University at Austin. UT Austin is highly diverse, ranking 161 in the United States for diversity (College Factual, 2019).

Likewise, Texas A&M University is highly diverse, ranking 357 for diversity (College Factual, 2019). I believed that the study population would yield a sample that would be a fair representation of the ethnic representation of preservice teachers in the United States.

The study was also delimited due to the size of the sample. The number of females (n=306) allowed for analysis, whereas the number of males (n=42) was not large enough to run a separate analysis. Additional groups that were too small to analyze separately included upper elementary preservice teachers (n= 72), middle school preservice teachers (n=61), African American preservice teachers (n=21), and Asian preservice teachers (n=56), preservice teachers seeking a math certification (n= 84), American Indian/Alaska native preservice teacher (n=1), preservice teachers seeking middle school certification (n=63), and preservice teachers seeking secondary certification (n=94).

The study was restricted to preservice teachers because it allowed for the sampling of a single generation of individuals and the results would represent the future of the profession Obtaining samples of all teachers would not provide much information because it would be a mix of different populations of teachers. This matters as older teachers may have been the result of previous education systems. Additionally, it is easier for teachers who are entering the profession to recall accurate information about mathematics rather than experienced teachers who have been in the field for some years. Sampling preservive teachers eliminates the variable of teachers forgetting content knowledge since college.

A further limitation of the research was using only Mathematical Self-Efficacy and Mathematical Self-Concept as a measure of Attribution of Expectancy. Typically, in SEM analysis, three measures are desired to measure the latent variable adequately (Bollen & Bauldry, 2011). Under identification of a latent variable may result in model misspecification. This specific study lacked a third measurable variable for Mathematical Attribution of Expectancy.

Finally, the study is delimited in the study design. As this research was not a longitudinal study, the study was overall limited on data collection. Specifically, this study lacked measured behavior over time resulting in the limited power of the study conclusions. Determining causality is limited in cross-sectional studies (Sedgwick, 2014; Setia, 2016). Additionally, as this study was correlational, the study cannot state conclusions about causality. The inability to determine causality leaves uncertainty about the predictive power of the model.

Assumptions

The key assumption of this study was that the indicators are a measure of latent variables. Specifically, this research considered both mathematical self-concept and mathematical self-efficacy as predictors for Mathematical Attribution of Expectancy. Additionally, this study assumed that all of the Subjective Task Values in the instrument represented all of the necessary measures of Mathematics Subjective Task Value. The study assumed that preservice teachers would obtain a teaching position at the reporting desired level of instruction. Finally, this study concluded that the response rates of the preservice teachers reflected the population of the entire K-12 preservice community.

Definition of Terms

The significant terms used in the study listed below, along with clarifying definitions.

Attainment: the importance the individual assigns to the task and how their performance on such will reflect on them as an individual (Artiles & Matusovich, 2020).

Attribution of Expectancy: specific beliefs individuals have regarding their progress on specific tasks they carry out in the short-term future or long-term future (Artiles & Matusovich, 2020).

Cost: the price of success or failure in terms of what the individual has to give up (Artiles & Matusovich, 2020).

Early-Primary School: defined in this study as grades kindergarten, first grade, and second grade (Timmons, 2021).

Expectancy-Value Theory (EVT): EVT is the model of motivation focusing on expectancy including ability beliefs, outlooks for success, and the component of subjective task value (Wigfield & Eccles, 2000).

Higher-Primary School: Defined in this study as grades third, fourth, and fifth grade (Wang et al., 2020).

Interest: the individual's enjoyment in the task (Artiles & Matusovich, 2020).

Math Self-concept: general perception a person holds about math ability, including attitudes, feelings, and knowledge (Marsh et al., 2019).

Middle School: Defined in this study as grades sixth through eighth (Wang et al., 2020).

Pedagogical Knowledge: the mathematical knowledge necessary to teach mathematics and consists of two components: knowledge of instructional strategies/representations and understanding of students' preconceptions and misconceptions in mathematics (Murray et al., 2018).

Preservice Teachers: students in an educational training program before undertaking any teaching (Manasia, 2020).

Secondary School: defined in this study as grades 9-12 (Thompson & Senk, 2020).

Self-Efficacy: one's belief in one's ability to succeed in specific situations or accomplish a task, typically domain-specific (Bandura & Walters, 1977).

Subjective Task Value: the people engaging in tasks that are valued (Artiles & Matusovich, 2020).

Utility Value: how useful the task is to the individual (Artiles & Matusovich, 2020).

Organization of this Study

This dissertation is organized into five chapters. The first chapter overviewes the statement of the problem, the purpose of the study, the theoretical foundation, including an introduction to the Expectancy-value Theory, and finally, the chapter included the research questions and hypotheses. The first chapter also presented an overview of the methodology, limitations, delimitations, and definitions used in the study.

The second chapter overviews the Predictors of Career Choice, including Gender and Career Choice, Predictors to Enter Teaching, Choice of Grade Level, Comparisons of Grade Level Teachers, Teacher Qualifications. Additionally, the researcher delineates measured variables starting with a theoretical framework outlining the Expectancy-Value Theory. Chapter 2 includes the specific measure of preservice teacher's Math Self-Efficacy, and Subjective Task Values. This study attempted an investigation of choice of preservice teacher career grade-choice using the Expectancy-value Theory.

Chapter 3 provides the justification of methodology and design of the study and a detailed explanation of the steps used to conduct the research. Chapter 4 provides an analysis of the data and provides answers to the research questions. Chapter 5 includes a discussion of the results, recommendations for practice, and suggestions for further research.

Conclusion

This research study draws on the Expectancy Theory to try to develop a model linking mathematics belief such as Mathematical Attribution of Expectancy and Mathematical Subjective Task Values to the motivation to explain career grade level choices of preservice teachers. Participants completed a survey incorporating questions from the instruments entitled *the Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale* and *The Mathematics Value Inventory for General Education Students*. In establishing a relationship between the Math Attribution of Expectancy and Subjective Task Values, this study explored the role of mathematics belief with preservice grade level choice.

Chapter 2

Literature Review

Introduction

I will base this chapter as the setting for the foundation of this research. First, I examine current research that explains teacher motivation to enter teaching. Second, I use the literature review to clarify current research to define the variables of the teacher's choice of grade level. Finally, I will explain the Expectancy Value Theory, and I explain the predictors of motivation in discussing Attribution of Expectancy, and address the relevant research related to Subjective Task Values. Finally, I summarize the research in the conclusion of the Literature Review.

Predictors of Career Choice

Individuals seeking employment must consider job opportunities and career prospects (Hodzic et al., 2015; Müller, 2020). Job opportunities are defined as short-term opportunities primarily to make money and are organization-specific, whereas career prospects represent long term life pattern (Sears, 1982). In garnering employment, some rely heavily on luck; others make deliberate career decisions (Guan et al. 2015; Hodzic et al., 2015). In making those career decisions, some of the predictors of career choice include personality type, skills and abilities, gender, and culture (Sieger & Monsen, 2015; van der Vleuten et al., 2016; Wang & Degol 2017). The motivations to explain career choice are addressed academically in career theories or models (Ball et al., 2017; Ball et al., 2019).

The initial career theory was first introduced by Ginzberg et al. in 1951 with the Theory of Career Development. The Theory of Career Development suggests that career decisions are a result of individual compromises due to reflections on ability and doubt related to the ability to make specific careers (Maree, 2018). These doubts lead to settlements of career aspirations and once committed, are permanently decided (Brown, 2002; Maree, 2018). Through the process of elimination of career paths opportunities, individuals settle on careers (Brown, 2002).

Since the 1950s, the evolution of career development theories has focused on the role of personality in career choice and how all factors relate to personality differences (Maree, 2018). The significant framework that links personality to career choice include Holland's (1997) Theory of Personality and Vocational choices, Super et al.'s (1996) Development Theory, Mitchel and Krumboltz's (1996), Theory of Career Counseling, and Dawis and Lofquist's (1996) Work Adjustment Theory. Each theory has a different approach and a specific lens to investigate motivations for career entry.

Holland's (1997) Theory of Personality and Vocation choices stated personality types influence choice of career. Holland argues that individuals seek out careers that are congruent with their personality type (Sheldon et al., 2020). Holland argued that there were only six personality types and those six factors were the sole determinate of a personal career. As humans and career choices are very complicated, this theory lacks precise predictive power (Spokane, 1985).

Super’s (1996) Development Theory stated that career development was a process of life development and personal characteristics with individuals seeking employment to express themselves and develop a self-concept. Super argued humans undergo five development stages with each related to their career. The growth-early childhood, ages four to 14; exploration late adolescent, 15-24; establishment, ages 25-44 years old; maintenance ages 45-65; disengagement, 65 and older. During exploration, late adolescent individuals develop ideas and become aware of limitations about one’s ability. During the establishment stage, one begins to prove their competence. Super argued that individual beliefs associated with ability and efficacy was a predominate factor involved in career choice. Individuals develop career paths due to self-awareness of capacity and available opportunity to refine career aspirations (Super et al., 1996). Some of the significant criticisms of Super’s theory is that the stages are culturally specific, and the theory suggests individuals with difficult career choices will stay in their career.

Mitchell and Krumboltz’s (1996) Theory of Career Counseling stated that career development was a result of life experiences developing both skills and reactions influencing career decisions. The Theory of Career Counseling is different from other theories in that it states that individuals develop skills through experience. The criticism of the Career Counseling Theory is that the underlying philosophy that the world is uncertain, and rather than career plan, individuals typically react to opportunities. For example, fields that require extensive training, such as law or medicine, require significant planning, and the Theory of Career Counseling does not explain these types of careers.

Dawis and Lofquist's (1996) Work Adjustment Theory (WAT) is a person-environment fit theory. WAT posits that work is an interaction between the environment and an individual. The constant need for the individual to do the task and the environment's requirement for the completion of the tasks is called correspondence (Strauser et al., 2020). Work adjustment is the positive relationship between satisfaction of the individual doing the job and the environment having the individual doing the job (Strauser et al., 2020). The main predictors of an individual staying with a career are personal satisfaction and flexibility, both of which are related to the personality of the individual (Strauser et al., 2020). Specific criticism of WAT is the inability to explain current modern career choices (Blau, 1993). WAT is unable to explain motivations for career jumpers (Blau, 1993).

Bandura (1977) developed the motivational theory of Efficacy versus Outcome Expectations. The focus of Bandura's explanation includes outcome expectation and efficacy expectation. Outcome expectations refer to the way an individual expects a specific behavior that leads to a particular outcome (Bandura & Walters, 1977). An efficacy expectation is an estimate that one can be successful in executing behavior to produce the desired result (Lent et al., 2017).

Predictors to Enter Teaching

I found many factors that influence teacher career selection, and currently, I find there is no exact consensus on what predicts whether an individual will enter teaching (Brookhart & Freeman, 1992; Dörnyei & Ushioda, 2011). However, common reasons for prospective teachers to enter the profession have largely remained unchanged over the decades. They include a desire to work with children or adolescents, a desire to impart knowledge, a desire to serve society, job security, optimal work schedule, compatibility of the demands of the jobs, and high-demand skills (Bastick, 2000; Han et al., 2016; Kyriacou & Coulthard, 2000; Olsen, 2008; Ribak-Rosenthal, 1994; Topkaya & Uztosun, 2012; Watt & Richardson, 2007).

Holland's (1997) Theory of Personality and Vocational Choices suggests that personality plays a role in career choice. Hollands's theory of personality fits well with the desires to enter teaching, but the criteria of personality and career choices are broad to predict individuals entering teaching accurately. As the teaching profession typically requires a bachelor's degree and specialized training, both Mitchell and Krumbholz's (1996) Theory of Career Counseling and Dawis and Lofquist's (1996) Work Adjustment Theory fail as models to adequately explain motivation to enter teaching. Super's (1996) Development Theory discusses the idea of ability and efficacy as a motivator to choose education, which matches the characteristics of incoming teachers. However, as teaching has high-attrition rates, Super's Development Theory is limited. Ginzberg et al. Theory of Career Development, which describes career motivation as an evaluation of individual talent, maybe a strong predictor of individuals entering teaching (Maree, 2018). Bandura's (Bandura & Walters, 1977) motivational theory of Efficacy versus Outcome expectations holds promise to provide an explanation of motivation in education. Self-beliefs are central in the career decision-making process. However, Lent et al. (2017) determined that efficacy alone has not been successful in predicting education career choices.

Preservice Teachers

One specific consideration I find for any theory predicting teaching as a profession must consider that individuals do not know the actual job until hired. As such, I assert researchers need to explore the attitudes and beliefs of individuals entering teaching to develop an understanding of motivation. I define preservice teachers as individuals enrolled in a teacher training program (Manasia, 2020). The characteristics of preservice teachers as I define them are specific. First, preservice teachers are confident in their ability to do the work of a teacher, such as explaining concepts, organizing ideas, or building useful lessons (Sinclair, 2008). Additionally, preservice teachers have a strong desire to influence society. According to Han et al. (2016), social justice is rated highly for incoming teachers and working with children provides an outlet to impact society. Finally, preservice teachers highly value the specific perks of teaching such as a fixed work schedule, regular vacations, including summer vacation and ultimately job security associated with a profession that needs teachers (Chiong, et al, 2017; Kraft et al., 2020).

I also found the profession of teaching has many downsides that would discourage many from entering the profession. Individuals choosing not to enter teaching include pay, the workload, respect, and perceptions of student behavior (Barnmby, 2006; Buchanan, 2010; Davidson, 2007; Greer et al., 2020; Quicke, 2018; Wood, 2019). Teachers also find the workload is undesirable (Birchinall, 2019; Parfitt, 2020). Finally, college graduates dedicated to earning a college degree have other career options that has higher pay and greater respect (Carver-Thomas & Darling-Hammond, 2017; Geiger & Pivovarova, 2018).

Choice of Grade-Level

Although research of teacher choice of grade level is not as extensive as other career motivations, strong evidence suggests the determination of grade level is like the choice of career with personality type, the perception of ability being the dominate factor (Akpe, 1991, kyriacou et al., 1999, Stellmacher et al., 2020). Additionally, gender is a a difference in primary and second teachers (Baye & Monseur, 2016; Makarova et al., 2019). Individually, factors such as subject level plays a roll as well (Akpe, 1991; Stellmacher et al., 2020)

I found research associated with differences in primary and secondary teachers suggest that the differences in the choice between these levels may be a combination of personality types and perceptions of the ability of preservice teachers (Kyriacou et al., 1999, Stellmacher et al., 2020). For example, a substantial factor in choosing to teach at the secondary level is the motivation to teach a specific subject (Kyriacou et al., 1999, Stellmacher et al., 2020). The motivation to teach these subjects is related to past academic performance in these subjects (Akpe, 1991; Stellmacher et al., 2020). In addition to the general enjoyment from the subject material, preservice secondary teachers anticipate utilizing their specialized skills teaching a single subject in secondary and prefer a job to use their content (Kyriacou & Coulthard, 2000; Stellmacher et al., 2020).

I have found research which indicates that a difference in teacher efficacy exists between primary and secondary. Primary teachers consistently report higher levels of Mathematical Teacher Efficacy (Eren & Tezel, 2010). Besides general math teaching attitudes between different levels, there is relatively little research on the interaction of mathematical ability beliefs and grade level choice. In one, Pearson (2012) found that for general mathematical confidence, there was no difference in the grade level. The major limitation of Pearson's study was that the researcher considered general confidence to teach at the anticipated level rather than general mathematical confidence.

Gender and Grade-Choice

I found in the body of literature extensive research on gender regarding teachers entering the profession. Researchers have examined the role of gender and entering the teaching profession for decades (Cushman, 2005; Herbst, 1989; Johnson & Birkeland, 2003; Muralidharan, 2016; Tašner et al., 2017). Gender is a factor in the desired grade level (Baye & Monseur, 2016; Makarova et al., 2019). The Bureau of Labor Statistics (2018) reported that in 2017, females predominately chose to teach lower grades. Specifically, the report found that 97.7% of preschool and kindergarten teachers were female; 79.3% of elementary and middle school teachers were female; and 58.5% of secondary teachers were female. Eren and Tezel research on motivation found that elementary and female teachers professed significantly greater teaching efficacy and a commitment to teaching (Eren & Tezel, 2010). Leech et al. (2019) pointed out that predominately female teachers perpetuate the perception that these roles are for females. Han et al. (2016) reported that the significant influence of primary preservice teachers is the motivation to work and influence children. These internal motivation factors to teach found in primary level teachers provides, at least partially, an explanation for teachers who choose grade levels in primary schools even though the pay is less than it is at the secondary level(Allegretto et al., 2018; Berlinski et al., 2020; Evans & Tribble, 1986).

Education is a traditionally female-dominated profession (United Nations Educational Scientific and Cultural Organization, 2011; Bureau of Labor Statistics, 2019). In a study by Bottia et al. (2015), the researchers found that education majors at the University of North Carolina were 56% female and 44% male. Bottia et al. suggested similar gender representation percentages nationally.

At different grade levels, gender differences become more pronounced. Men are increasingly entering the profession, but the percentage of women entering teaching is increasing at a higher rate (Bureau of Labor Statistics, 2021). The past few decades, Americans experienced changes in social expectations of gender with women increasingly entering the workforce (Bureau of Labor Statistics, 2021). The Bureau of Labor Statistics (2011) nearly a decade ago showed that the percentage of female physicians, lawyers, and architects had increased three to five fold from 1972 to 2011, with the numbers leveling out since (Bureau of Labor Statistics, 2021). As women entered the workplace, men were required to compete with women, possibly creating workplace perceptions of teaching as a more comfortable career to enter and succeed, particularly for women (Bureau of Labor Statistics, 2021).

I assert that any consideration for a motivation theory of desired grade level would require the inclusion of gender. Considering the significant underrepresentation of females at the secondary level (Bottia et al., 2015), especially in terms of STEM teaching (Watt et al., 2012), combined with known differences in academic self-efficacy (Huang, 2013) the research suggest that primary teachers are making career choices to avoid more challenging careers at the secondary level. Overall, either actual ability or beliefs of ability are influencing the choice of grade-level for gender.

Ethnicity and Grade Choice

I found in the body of research that education has a severe ethnic imbalance in grade-level teachers. Although there is an underrepresentation of ethnic minorities overall, racial teacher imbalance is most prominent in the lower grades much akin to the gender imbalance (Bureau of Labor Statistics, 2018). When considering ethnicity, in 2017, Caucasians/Whites represented 77.1% of preschool and kindergarten teachers, 85.2% of elementary and middle school teachers, and 86.2% of secondary teachers (Bureau of Labor Statistics, 2018).

There does not appear to be a definitive explanation in the literature for ethnic differences in grade level choices. Self-efficacy is a predictor of both confidence and ability and can help explain career choices (Penn & Lent, 2019; Sharma & Suri, 2019). Ethnic minorities such as African American, Asian/Pacific Islander, and Latino/students are found to have lower levels of STEM Efficacy (Andersen & Ward, 2014; Gottelib, 2015; Sheu et al., 2018). Research from Leech et al. (2019) suggested that traditionally low representation of teachers and underqualified teachers in urban school plays a role in lower academic ability and efficacy (2019). Like gender, a motivation theory that explains minority grade level choice would need to consider ability beliefs such as self-efficacy.

Certification Requirements

I note that State Board of Educations are responsible for establishing certification requirements (Higher Ed Texas, 2021). In the state of Texas, teaching candidates have different certification requirements. For instance, certification in fourth to eighth grade Mathematics, and seventh to 12th grade Mathematics requires 15 credit hours of college work in math courses (Texas Education Agency, 2020; University of Houston, 2019). Science certification in fourth to eighth grade and seventh to 12th grade requires 15 credit hours in a science with required courses in Chemistry, Biology, Geology and Science (Texas Education Agency, 2020; University of Houston, 2019). A certification in EC-6 generalists require 12 specific credit hours (Texas Education Agency, 2020; University of Houston, 2019). Individuals obtaining specialized certifications are required to meet specific grade point averages (GPA) in a content area (Texas Education Agency, 2020; University of Houston, 2019). In addition to specific courses, candidates are required to pass specific tests of specific content knowledge (University of Houston, 2019).

In my research of literature, I found that previous research had not used EVT to explain the motivations for grade level choice in education. I anticipate this study will address the motivation of grade choice level of preservice teachers by applying EVT to address whether individual beliefs of ability in the domain of mathematics explains the choice of grade level. As a theoretical framework, researchers have successfully implemented the EVT to predict and explain motivation and behavior (Ball et al., 2017; Ball et al., 2019; Barron & Hulleman, 2015; Wu & Fan, 2017). DeJong and Fawcet (1981) defined motivation as a function of the value an individual placed on specific goals and the perceived likelihood that a particular behavior will lead to those goals. A key aspect of motivation is that motivation and performance ability are linked (Eshak et al., 2015; Gillet et al., 2013).

I found that EVT is succeessful in explaining the motivational foundation for both advanced educational opportunities and career paths (Lauermanne et al., 2017). Previously, the Expectancy Value Model has been used to predict student career choices in fields of mathematics with researchers finding a correlation between mathematical attitudes and course selection in middle and high school (Meece et al., 1990). Additionally, EVT has demonstrated a substantial role in explaining adult career choices Lauermann et al., 2017; Song et al., 2017).

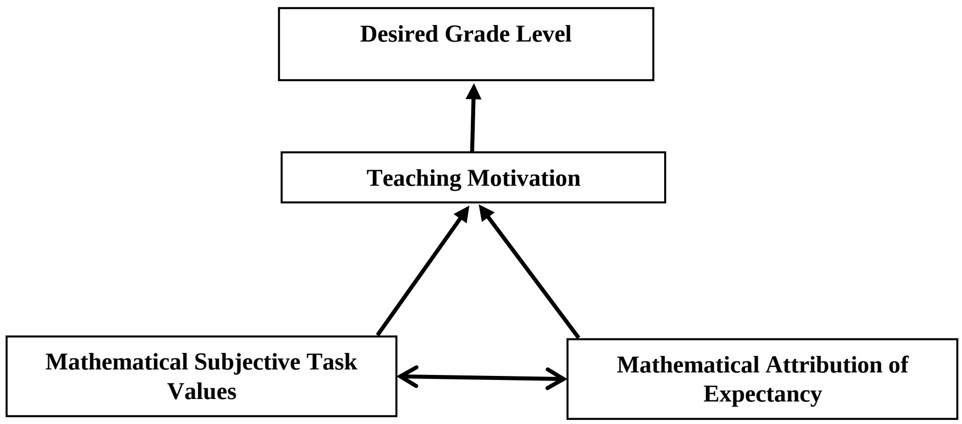
In the research of modern theories of motivation, I found many factors that related to satisfaction or perceptions of satisfaction—See Theory of Work Adjustment or Social Cognitive theories—in which achievement is a significant factor. Additionally, Bandura (1977) described self-efficacy as a determinate of career motivation theory. A theory which includes self-efficacy to explain motivation would explain the unequal representation of both gender and ethnicity in K-12 teachers (Bandura & Walters, 1977). Additionally, such a theory would provide consideration of whether primary teachers are open to teaching secondary as much as primary but stay due to mathematical beliefs. A difference in mathematical attitudes, especially among primary preservice teachers, would suggest that avoidance of more challenging careers is the basis of career choice.

Theoretical Framework

The theoretical framework of my study is based on the Expectancy Value Theory (EVT). EVT is a motivational theory originally proposed Eccles (1977). EVT emerged as a way to explain motivations in both academic and non-academic domains, such as music or sports. In the 1980s, researchers applied EVT to education to clarify academic achievement (Ball et al., 2017; Ball et al., 2019; Wu & Fan, 2017). EVT posits that a combination of competency beliefs and value beliefs are the primary motivation for people to provide effort and succeed in a domain (Eccles et al., 1983). Eccles originally stated that motivation to engage in activity has two core theoretical constructs, Attribution of Expectancy, and Subjective Task Values. Attribution of Expectancy is the expectation of being successful in doing an action. Subjective task value relates to the perceived value of engaging in a task. Figure 1 is a representation of the theoretical foundations.

Figure 1

Expectancy Value Theory Theoretical Model



Attribution of Expectancy

In my research of the Expectancy Value Theory, I found one of the two most significant factors towards motivation is Attribution of Expectancy Values. Attribution of Expectancy is an individual's belief in the likelihood of success in an upcoming task or activity (Artiles & Matusovich, 2020). Attribution of Expectancy is a latent variable and not measured directly. As such, my research requires a measurable variable that reflects the Attribution of Expectancy. In my research, the measure of Attribution of Expectancy is Mathematical Self-Efficacy and Mathematical Self-Concept. Self-efficacy originally defined by Bandura (1977) as the expectation of success in doing a task (Bandura & Walters, 1977). As such, in my study, the specific efficacy domain used to measure mathematical expectations is mathematical self-efficacy. Additionally, my selection of self-efficacy as a predictor of Expectancy Values is appropriate as previous research establishes self-efficacy as a reliable measurement of Expectancy Values (Green et al., 2017; Martin & Desmond, 2018).

I found in previous research that self-efficacy beliefs are a fair representation of competency (Stajkovic & Luthans, 1998). Self-efficacy beliefs are the individual beliefs to accomplish tasks and are the foundation of generating human competence (Bandura & Walters, 1977). Self-efficacy beliefs are directly related to positive academic outcomes as individuals with higher perceived Self-Efficacy tend to set higher goals and have a firmer commitment to them (Bandura & Wood, 1989; Multon & Brown, 1991).

I found four sources of self-efficacy beliefs. According to Bandura (Bandura & Walters, 1977), these four sources are Enactive Mastery Experiences; Vicarious Experiences; Verbal Persuasions and Allied types of Social Influences; Physiological and Affective States. Vicarious Experience relates to individual beliefs gained through the attainment of others (Bandura, 1997; Bandura & Wood, 1989). As others with similar ability can accomplish a task, the observer builds confidence to attempt the task. Verbal Persuasion relates to verbal praise and persuasion to achieve a task (Bandura, 1997; Bandura & Wood, 1989). Physiological and Affective States relates to physiological responses such as sweating and mood, which influences personal confidence (Bandura, 1997; Bandura & Wood, 1989). The most critical source of efficacy is Enactive Mastery Experience. Enactive Mastery Experience is the idea that the development of efficacy occurs through self-evaluation, the perception of task difficulty, required effort expenditure, and self-monitoring of ability (Bandura, 1997; Bandura & Wood, 1989).

I found the main limitation of educational research associated with self-efficacy is the conflation of different domains. Teacher Self-efficacy relates to a teacher's perceived ability in undertaking specific teaching tasks (Liu, 2021). Previous research on teacher self-efficacy has found that Mathematical Teaching Efficacy has been reported to be most significant in early childhood education and decreases the higher the grade level (Pendergast et al., 2011). Self-efficacy logically would be more significant in primary teachers when considering research has identified primary teachers as having greater intrinsic teaching motivation (Eren & Tezel, 2010; Klaeijsen et al., 2018).

My main concern with Mathematical Teaching Efficacy is that this is not an accurate reflection of one's confidence in mathematical ability. Whereas Mathematical Teaching Efficacy is the confidence in being a Teacher of Mathematics, Mathematical Efficacy is individual confidence to succeed in mathematics. Previous research investigating teacher efficacy centered on mathematical teacher efficacy (Gibson & Dembo, 1984; Tschannen-Moran et al., 1989). Previous studies have conflated Mathematical Teacher Efficacy with Math Efficacy (Skaalvik & Skaalvik, 2006; Swars, Daane, & Giesen, 2006). Studying Mathematical Efficacy allows the study to explore the role of mathematics in teacher career choice directly.

Additionally, I have concerns about the role of math ability in different grade levels. As the middle school and secondary teacher only works in the framework of a single individual subject, the previous research seemingly failed to recognize that concerns about math ability (Gibson & Dembo, 1984; Tschannen-Moran et al., 1989) would neglect to address that primary teachers teach a myriad of factors which may play a role in their math teaching efficacy. Measurements of secondary math teachers may reflect concerns of teaching an individual subject, including matters of different curricula. Furthermore, as primary teachers have students lacking any prior math knowledge and secondary teachers need students with years of previous math knowledge, comparisons of teaching efficacy in the domain of mathematics would not be appropriate because secondary teachers receive students of different abilities. This means teachers are required to provide specific interventions including differentiation.

To reduce the errors associated with measuring Attribution of Expectancy, my study included Math Self-Concept as a measure of Attribution of Expectancy. Math Self-Concept is general perception a person holds about math ability, including attitudes, feelings, and knowledge (Marsh et al., 2019). Math research has focused heavily on the relationship between math self-concept and individual math achievement, with results generally showing a positive relationship (Arens et al., 2017; Susperreguy et al., 2018; Timmerman et al., 2017). Previous research that has looked at math efficacy has included measures for self-concept as well (Brisson et al., 2017; Bong & Skaalvik, 2003; Cooper et al., 2018).

Subjective Task Values

In my research of EVT, I found that Eccles (1983), when developing Expectancy Value Theory, was not able to predict motivations based on

Attribution of Expectancy alone. Eccles and his colleagues included the concept of Subjective Task Value to describe individual motivations to engage in a specific behavior. Subjective Task Values consist of four sub-constructs: Attainment Value, Intrinsic Value, Utility Value, and Cost (Eccles, 2005; Eccles, 2009; Lauermann et al., 2017). Utility value is about the value one associates with doing the task for future goals, such as additional studies or a career (Artiles & Matusovich, 2020); Intrinsic value is the individual's enjoyment of or interest in doing the task (Artiles & Matusovich, 2020). Attainment is about the value or importance of one's self-identity for doing the task (Artiles & Matusovich, 2020).

Cost is related to the decision of doing the task and how that affects one's ability to do other tasks (Artiles & Matusovich, 2020). For example, a student wanting to be a doctor would find high value in doing the task of studying that is utility value. Another example is an athlete considering his or her identity as a great athlete would find high value in working out is an example of attainment. On the other hand, an individual who finds the Civil War fascinating and enjoys the task of reading books about the Civil War is an example of Intrinsic Value. A graduate student choosing to spend the needed money to do the task of auditing a class to improve his or her skill is an example of cost.

Application of Expectancy-Value Theory

The Expectancy Value Theory addresses the fact that motivation is multi-faceted. EVT considers both beliefs about individual ability and the value of engaging in the task. In building an SEM model including both Attribution of Expectancy and Subjective Task Values of mathematics, my research is attempting to determine if mathematics is a motivation involved in grade-choice level.

The following four hypotheses, all supported by the conceptual framework established in the literature review, guide the purpose of my research:

$H1_1$: Items 1-6 are indicators for the first-order latent variables Mathematical Self-Efficacy; items 7-10 are indicators for the first-order latent variables Mathematical Self-Concept; items 11-17 are indicators of the first-order latent indicator Interest; questions 18- 24 are indicators of the first-order latent variable General Utility; items 25-31 are indicators for the first-order latent variable Need for High Achievement; items 32-38 are indicators of the first-order latent variable Personal Cost.

$H1_2$: Mathematical Self-Efficacy has a positive effect on Mathematical Attribution of Expectancy; Mathematical Self-Concept has a positive effect on Mathematical Attribution of Expectancy, Interest has a positive effect on Mathematical Task Values; General Utility has a positive effect on Mathematical Task Values; Need for High Achievement has a positive effect on Mathematical Task Values; Personal Cost has a positive effect on Mathematical Task Values.

$H1_3$: The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical Attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical Task Values are dependent on gender, such that the effect of Mathematical

Attribution of Expectancy and Mathematical Task Value is stronger when the gender is female.

H1$_4$: The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical Attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical Task Values are dependent on ethnicity, such that the effect of Mathematical Attribution of Expectancy and Mathematical Task Value is stronger when the ethnicity is Caucasian/white.

Conclusion

The literature review of my study included research relating to career choices, including the choice of grade-level and gender. As secondary teaching is more content centered and is seen as more labor-intensive, looking through the lens of the Theory of Career Development (Maree, 2018), and Bandura's (1977) Motivational Theory of Efficacy versus Outcome Expectations, individuals lacking confidence in their abilities would have avoidance motivation towards such grade levels and focus on lower grades which require less competence. In terms of mathematics, lower elementary grades would need less math competency.

At the other end of the spectrum, people who believe they have stronger capabilities in math would embrace extrinsic motivations such as higher pay and respect for teaching advanced subjects. Likewise, the constructs of the EVT model are like the SCCT interest model as both link self-efficacy expectations and outcome expectations to predict career models (Lauermann & Eccles, 2017;

Maree, 2018). In terms of gender, research suggest females have lower self-efficacy in mathematics (Tellhed et al., 2017), and as a result, they may avoid more challenging careers in favor of more comfortable positions.

My research strives to provide a more solid foundation of mathematical comparisons of teachers at different levels. Specifically, this research is attempting to use the Expectancy Value Theory to address the role that mathematics influences motivation for preservice teachers' career choice of grade-level to teach. Through the Expectancy Value Theory, my study measured Math Self-Efficacy and Math Self-Concept as Attribution of Expectancy and measured four subjective task values to approximate Math Task Value to model the influence of grade-level choice.

My research strives to determine the role of these variables and the distribution of preservice teacher in the K-12 individually, as previous research is limited. Lastly, demographic data shows an unequal representation of females and minorities in lower-primary levels (Bureau of Labor Statistics, 2021). I found previous research identified that subject specificity is a trait of secondary teachers whereas my study investigated whether mathematics played a role in career placement for these populations.

Chapter 3

Methodology

Introduction

The purpose of my study was to examine the motivations of pre-service teachers to consider teaching a grade level and the related associations with gender and ethnicity/race. To achieve the previously stated purpose, I utilized established research in education, psychology, and sociology to operationalize motivation. In this chapter I will explain the methodology used. First, I expound on the research design, describing the type of research carried out, including the research questions and hypotheses. Next, I provide information about the participants, including participation and selection. Then, I discuss the research instruments and measures used. I follow with with data collection procedures, and then statistical analysis, treatment of data, and the data analysis. Finally, I discuss the study design, including validity, reliability, and ethical considerations.

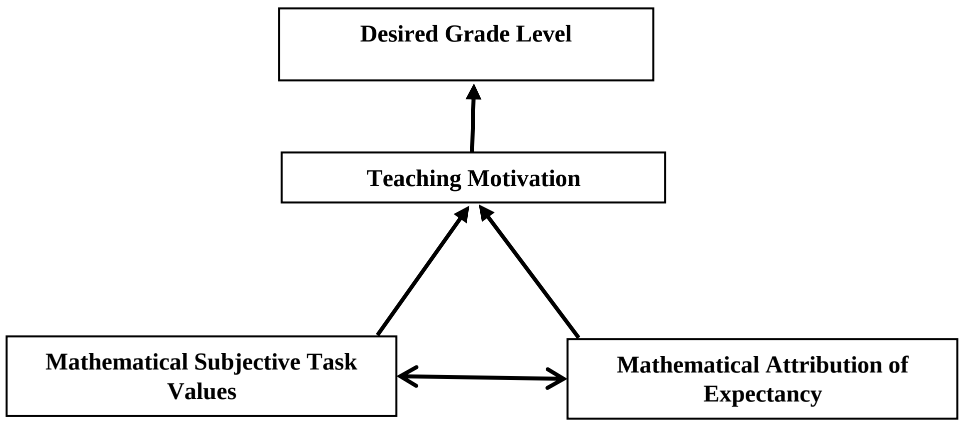
Study Design

My study utilized a non-experimental, cross-sectional causal-comparative design to answer the questions about pre-service teachers' choice of grade level. My study is non-experimental due to the lack of participants in a treatment or control group, and the statistical models test for correlations or associations between purported predictors and grade-level choice (Seeram, 2019). My study is cross-sectional due to the investigation of outcomes of different populations at the same time (Sedgwick, 2014; Setia, 2016).

My study includes a recursive structural equation model. A recursive structural equation model only includes unidirectional causalities, not allowing feedback loops (Cortina, 2005). Figure 2 depicts my theoretical model for the study.

Figure 2

Theoretical Model



My model hypothesizes the parameters for Mathematical Task Value is a positive relationship with the grade-level choice. My model hypothesizes the parameters for Mathematical Expectancy Value have a direct positive relationship with the grade-level choice. I will test the models for preservice teacher subpopulations of ethnicity/race, gender, and math certification.

Participants

Participants for my study included pre-service teachers at public universities in the Houston region. The criteria for inclusion included (1) current undergraduate study at any grade-level; (2) enrolled in an educator preparation program; (3) not currently employed as a teacher; (4) at least 18 years old. Specially, all individuals who were enrolled during the 2019 fall semester at one of the University of Houston System campuses, the University of Texas at Austin, or Texas A&M University were invited to participate. Second, my study required potential subjects to be enrolled in an educator training program to enter the teaching profession.

Recruiting potential subjects for my study required an extensive sample size. Research from Wolfe et al. (2013) used a Monte Carlo simulation and multiple CFAs with one, two, and three latent factors, indicated by four, six and eight indicators. The authors specified minimum statistical power at 80% and rejected models with lower power. The measurement model was just-identified, and the simulation study varied the magnitude of standardized factor loadings (from .50, .65, to .80) and also the degree of model misspecification.

The authors suggested that a confirmatory factor analysis with 5-10% missing data required at least 250 subjects. That said, university external response rates for a survey are low, with one study identifying the response rate at around 14% (Porter & Umbach, 2006). Given the reality of low response rates, I recruited almost the entirety of the 356 subjects from the University of Houston, the University of Texas Austin, and Texas A&M University. I selected the rest of the participants from local public universities in Houston. The size of the teaching programs at these universities allowed for an opportunity for extensive recruitment from the population.

Although universities do not report the number of students enrolled per major, the universities report the graduates per major, which is an indicator of the size of student majors. The University of Houston system had 3,019 students enrolled in a teaching program in Spring 2019 (The University of Houston, 2019; University of Houston-Downtown, 2019; University of Houston—Clear Lake, 2019; University of Houston Victoria, 2019) the University of Texas Austin states 2,668 students enrolled in the College of Education in 2018 (University of Texas Austin, 2019) Texas A&M reports 6,942 students enrolled in the College of Education and Human Development in 2017 (Texas A&M University, 2019).

Table 1

Recruitment Populations at Targeted Universities, 2019 Estimates

University	**Education Majors**
The University of Houston-Victoria	247
The University of Houston-Downtown	422
The University of Houston-Clear Lake	533
The University of Houston (Main Campus)	1817
The University of Texas-Austin	2668
Texas A&M University	6942

Data Collection

I collected the data using an online survey. I sent education majors at the participating universities an email with a link to the survey. Access to my survey lasted for 50 days total. Additionally, I distributed posters and flyers in the education departments at the selected universities to provide awareness of the study. The advertising included a general-purpose for the research and advertised a raffle for five $100 gift cards for recruitment. I send an email with the study results to the participants who provided me an email after the completion of the study.

I provided subjects access the study survey on the *Qualtrics* platform. Participation was considered voluntary. I ensured participants agreed to a waiver to participate in the study. Data collected is stored on the *Qualtric*s platform and my (the primary researcher) personal computer. Only I have the password to access the survey results. Furthermore, subject identification is confidential as I kept no personal information on the participants.

Research Instrument

My survey for this study included selected items from *The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale* (Lee, 2009); The *Mathematics Value Inventory for General Education Student* (Luttrell, et al., 2010); and questions about age, ethnicity, gender, and grade-choice level that were adjusted from specific individual studies from the National Center of Science Education (Kramer et al., 2009). My study items are supported from research highlighted in Chapter 2.

The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale

The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale is an instrument that utilizes five Math Self-Concept items with a rating scale in 4-point Likert-type responses (4- Very Confident, 3- Confident, 2- Not Confident 1- Not Very Confident). The survey measures Math Self-Efficacy with six items using 4-point Likert-type responses (4- Strongly Agree, 3- Agree, 2- Disagree, 1- Strongly Disagree) (Lee, 2009). Appendix B has samples of the *Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale*.

Validity refers to the "degree to which test respondents view the content of a test and its items as relevant to the context in which the test is being administered" (Holden, 2010, p. 437). The validity of the individual items is partially ensured with the phrasing of Likert-style questions in both a positive and negative aspect, allowing individuals to provide more accurate responses. For the *Mathematics Self-Concept, Self-Efficacy and Anxiety Scale* the validity of the question was developed through particular test developers such as ACER, the Citogroup, and the NIER teams developing the mathematics items in multiple areas such as Australia, the Netherlands and Japan (Programme for International Student Assessment, 2006).

Previous definitions of reliability include the extent to which studies can be replicated, using similar methods, and getting similar results; the degree to which data are independent of the accidental circumstances of the research (Clonts, 1992). *The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale* was previously tested and found to be very reliable (Lee, 2009). All questions used in this study already passed peer-review and supports the validity of the instruments.

The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale instrument has undergone extensive testing by The Organisation for Economic Co-operation and Development with researchers validation testing in more than 40 countries (Luttrell, et al., 2010). *The Mathematics Self-Concept, Self-Efficacy, and Anxiety Scale* had a Cronbach alpha calculated for reliability. Cronbach alpha coefficients for scores on the two subscales were as follows: Math Self-Concept

(4 items), (median); (United States); Math Self-efficacy (6 items), (median); (United States) (Organization for Economic Cooperation and Development, 2005). Table 2 list all values Cronbach alpha coefficients calculated for Math Self-Efficacy and Math Self-Concept questions of each country.

Table 2

Cronbach's Alpha for Indices on Self-related Cognitions

Country	Math Self-Efficacy	Math Self-Concept
Australia	.86	.89
Austria	.80	.89
Belgium	.82	.89
Canada	.85	.91
Czech Republic	.80	.89
Denmark	.83	.90
Finland	.85	.92
France	.78	.89
Germany	.81	.91
Greece	.75	.86
Hungary	.82	.81
Ireland	.87	.93
Ireland	.81	.39
Italy	.78	.91
Japan	.87	.88
Korea	.87	.88
Luxembourg	.82	.89
Mexico	.80	.78
Netherlands	.83	.90
New Zealand	.86	.87
Norway	.84	.90
Poland	.82	.87
Portugal	.82	.89
Slovak Republic	.83	.87
Spain	.81	.89
Sweden	.85	.89.
Switzerland	.82	.90.
Turkey	.85	.88.
United Kingdom	.86	.88
United States	.86	.89
Brazil	.79	.83
Hong Kong-China	.87	.89
Indonesia	.74	.75
Latvia	.78	.85
Liechtenstein	.81	.89
Macao-China	.81	.89
Russian Federation	.80	.81
Serbia	.79	.83
Thailand	.84	.78
Tunisia	.79	.88
Uruguay	.82	.88

Note. Adapted from the Organization for Economic Cooperation and Development (OECD), 2005 PISA 2003 Technical Report.

The Mathematics, Value Instrument Inventory for General Education Students

The Mathematics, Value Instrument Inventory for General Education Students is an instrument used to measure Mathematical Task Values. The Mathematics Value Inventory for General Education Student utilizes 28 items with a response scale ranging from a 4-point to a 5-point Likert-type response to measure four primary dimensions: Interest, General Utility, Need for High Achievement, Personal Cost (Luttrell, et al., 2010). Interest is measured by seven items using a 4-point Likert-type responses (4- Strongly Disagree, 3- Disagree, 2- Agree, 1- Strong Disagree); General Utility is measured by seven items using a 5-point Likert-type responses (5- Strongly Disagree, 4- Somewhat Disagree, 3- Neither Agree nor Disagree, 2- Somewhat Agree, 1- Strongly Agree); Need for High Achievement is measured by seven items using a 5-point Likert-type responses (5- Strongly Disagree, 4- Somewhat Disagree, 3- Neither Agree nor Disagree, 2- Somewhat Agree, 1- Strongly Agree); and Personal Cost is measured by seven items using a 5-point Likert-type responses (5- Strongly Disagree, 4- Somewhat Disagree, 3- Neither Agree nor Disagree, 2- Somewhat Agree, 1- Strongly Agree). The questionnaire was designed online so that the respondents would click on a box in a position on the survey. Appendix B has samples of the *Mathematics Value Inventory for General Education Students Scale*.

The Mathematics Value Inventory for General Education Students Scale instrument initially underwent reliability testing. *The Mathematics Value Inventory for General Education Students* had a Cronbach alpha calculated for reliability. Cronbach alpha coefficients for scores on the four subscales were as follows: Interest (9 items), Utility (6 items), Attainment (6 items), and Personal Cost (6 items). All values are within an acceptable range (Organization for Economic Cooperation and Development, 2005).

Measures

My research questions allow for a precise definition of latent and observed variables in the study. The two main factors in the Expectancy Value model are Attribution of Expectancy (AE) and Subjective Task Values (STV). Both AE and STV are latent variables, meaning that they cannot be measured directly, and are endogenous, meaning they are dependent on other factors within the model (Xu, 2021). As both AE and STV cannot be directly measured, the research required an approximation of AE and STV with latent constructs measured through other measurable variables. Table D1 provides the hypothesized first-order latent factor and the latent factor on which the item is posited loading items to the first-order latent constructs.

Demographics

The survey section on demographics obtained subject demographic information. The items asked the subject to state their age, identify their gender, and identify their race/ethnicity. The researcher coded gender as “1” for female, and “0” for male. For the race/ethnicity variable, my research attempted to investigate the effect of being a minority and the choice of grade-level, as the research identified minorities are underrepresented in high-grade levels (Bureau of Labor Statistics, 2018). As such, my study analyzed ethnic and racial minorities. The researcher coded ethnicity/race “1” for Caucasian/White, and “0” for non-White or other and “3” for Asian.

The career measures section had items related to career goals post-graduation and served to provide questions about study participation and desired grade level. The first question asked the participant about their enrollment in an education program pursuing a bachelor’s degree. Participants who responded with *no* were directed to a question asking if the potential subjects were enrolled in a Master of Arts in Teaching (MAT) program. Respondents who selected no were directed to a question asking whether the potential candidates were enrolled in an alternative certification. Participants who answered *no* were directed to the end of the survey and were not able to answer further questions.

The following question is the desired grade-level question. The desired grade-level question in the survey has four options: (1) K-2 Grades (Lower Primary), (2) 3-5 Grade (Upper Primary), (3) 6-8 Grade (Middle School), (4) 9-12 Grade (Secondary School). The desired grade level question was coded K-2 Grades (Lower Primary) “0”, 3-5 Grade (Upper Primary) “1”, 6-8 Grade (Middle School) “2”, 9-12 Grade (Secondary School) “3”. Lower primary was labeled “0”, Upper Primary was labeled “1”, middle school was labeled “2”, and secondary school was labeled “3”.

Individuals who chose lower primary or upper primary answered a question on whether they planned to pursue a job as a specialist or a non-specialist. A specialist was coded as “1”, non-specialist was coded as “0”. Individuals were given the option to choose either a specialist at the primary level or if they chose the middle school or secondary school level were provided questions asking if they planned to teach mathematics. Individuals opting to teach mathematics were coded “1”; individuals opting not to teach mathematics were coded “0”.

Statistical Analysis

Research questions 1-3 were examined using structural equation modeling (SEM) (e.g., Kline, 2010), described below in more detail. Preceding the primary SEM analyses, I examined descriptive statistics to determine the mean, standard deviation, and frequency of all reported variables of interest. In addition, I examined the skewness/kurtosis of the measures, the correlation coefficients and the missing data patterns in SPSS using Little’s Missing Completely at Random (MCAR) Test. Little’s Missing Completely at Random test is commonly used to evaluate whether the MCAR assumption is tenable for the data at hand (Little, 2013).

The next section outlines the primary analysis portion of this study. First, I discuss the SEM analysis, including the χ^2 model test. The following section discusses the structural model including the confirmatory factor analysis. Next, I discuss the fit indices such as absolute fit index and the relative fit indices.

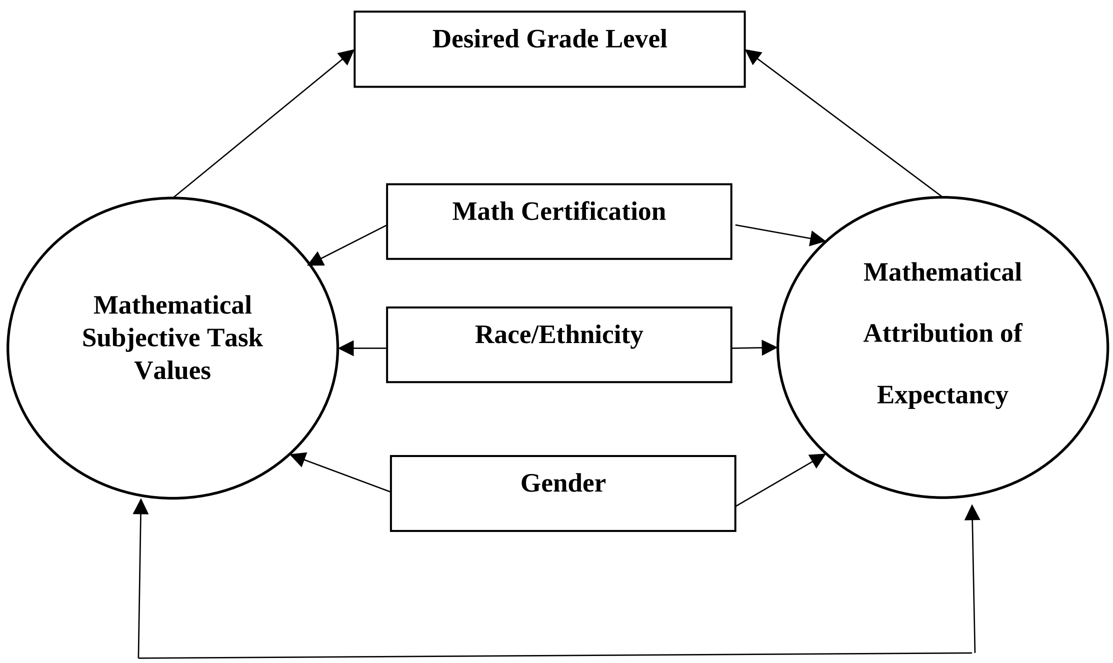
SEM Analysis

Structural Equation Modeling (SEM) is a comprehensive statistical method to test hypotheses about relationships between observed and latent variables or a technique for estimating, representing, and testing a theoretical model of linear relations among observed and latent variables (Suhr, 2019). The underlying assumption of an SEM analysis requires the relationships between the variables to be linear (Klein, 2011). The use of latent variables in the model allows the researcher to account for measurement errors in the study. Additionally, SEM requires larger sample sizes compared to traditional studies (Boomsma & Hoogland, 2001; Kline, 2011; Loehlin, 1998). In the case of this study, the ideal sample size to analyze and compare the individual models was at least 250 participants, however; a minimum sample size of 100 is required (Boomsma & Hoogland, 2001; Kline, 2011; Loehlin, 1998).

After determining the best measurement model, I conducted a structural regression analysis in SEM to examine the role of mathematical beliefs in preservice teacher motivation to choose a specific grade-level. A SEM model with a good fit between the Attribution of Expectancy, Mathematical Task Values, and grade-level choice as a mediator, according to the Expectancy Value Theory, would indicate postive mathematical beliefs and consequently, individuals who chose the grade level had motivations towards mathematical academic behavior. The model of SEM is depicted in Figure 3.

Figure 3

SEM Model



Confirmatory Factor Analysis

Before the hypothesized latent variable model shown in Figure 3 can be tested I must establish a measurement model. The measurement model links the latent variables to the observed variables and was tested using Confirmatory Factor Analysis (CFA).. The hypothesized CFA model presented in Figure 4 has two second-order latent variables and six first-order latent factors. Specifically, the following factor structure was tested: (1) Mathematical Attribution of Expectancy to the two first-order latent factors (Mathematical Self-Concept and Mathematical Self-Efficacy), (2) Mathematical Task Values to the four first-order latent factors (Personal Cost, Need for High Achievement, General Utility, Interest), (3) the six first-order latent variables to the 38 items. I ran the CFA analysis in R-software with the Lavaan package 6-.05 (Rosseel, 2012) and reported the results. Figure 4 establishes the depicted hypothesized CFA model.

Figure 4

Confirmatory Factor Analysis Model

An analysis of the data determines the type of estimator used in this study. The ML is a method of establishing distribution parameters through maximizing a likelihood function (Chen et al., 2019; Permai et al., 2018). The maximum likelihood estimation requires the data are both continuous and follow a normal distribution. To ensure the data met the assumptions for a maximum likelihood estimation, I determined the likelihood function through R-software, specifically Lavaan 6-.05 with different iterations finding the most stable values.

The descriptive statistics such as means, standard deviations, kurtosis and skewness and correlation coefficients were reported in Table 4. In this study a value beyond plus/minus two for skewness (Trochim & Donnelly, 2006; Field, 2009; Gravetter & Wallnau, 2014) and plus/minus five for Kurtosis is considered non-normally distributed (Benter, 2006; Ryu, 2011). During the analysis the skewness of specific loadings for General Utility, specifically loadings 1, 2, 3, 4, 5 were found beyond the state accepted standards for the Maximum Likelihood Indicator. Since the values were beyond the values for normality assumption required a maximum likelihood estimator, an alternative estimator was required. A common alternative for ML when the normality assumptions are not met is the Maximum Likelihood Estimator (MLR) with robust standard errors and a Satorra-Bentler scaled test statistic (Alberto Maydeu-Olivares 2017). The Satorra Bentler provides a scaled difference test statistic to calculate an approximately scaled chi-square statistic (Santorra & Bentler, 2001).

In addition, I examined the residuals to screen for potential local misfit. To screen for implausible parameter estimates, I investigated the data for Heywood cases, which are negative variance estimates, or out-of-range standardized estimates, that is, standardized values greater than one. Heywood cases occur due to certain conditions (Kolenikov Bollen, 2007). Nonconvergence is the situation where the maximum likelihood function fails to find a minimum fit function. Standardized values greater than one may indicate a correlation near one, unreasonable model constraints imposed, or model misspecification (Anderson et al., 1987; Chen et al., 2001; Jöreskog, 1999; Kolenikov Bollen, 2007)**.**

SEM Fit Evaluation

SEM model testing requires robust testing called Fit Indices to analyze model fit. The χ^2 test alone cannot be used to evaluate the models due to the limitations of the test, such as the sensitivity to the sample size (Yuan & Chan, 2016). Researchers have developed alternative tests of model fit, allowing for greater variety in tests for model fit (Hooper et al., 2008). The two types of fit indices in this research are the Absolute Fit Indices and Relative Fit Indices. SEM does not have a single criterion for theoretical model evaluation. Instead, a wide array of fit indices were developed (Ding et al., 1995; Schermelleh-Engel et al., 2003; Sugawara & MacCallum, 1993). In addition to fit criteria, standardized residuals greater than 2.58 (at a nominal alpha level of $p<.01$) were considered outside the appropriate range.χ2 Model Test The χ^2 model test assesses the overall fit and discrepancy between the observed and fitted covariance matrices. The χ^2 tests for the exact fit of the model and represents the plausibility of the null hypothesis, which states the tested model fits perfectly. The χ^2 test considers both the degrees of freedom and a p-value to calculate expected values. This specific research concluded a model as tenable with a p-value > 0.05 (Meyers et al., 2006).

The limitation with the χ^2 test is that first, it provides a binary solution of fit or non-fit and does not give a quantifiable the degree of fit (Barrett 2007). Second, the χ^2 probability value is insufficient to provide a measurable explanation of the model fit (Barrett, 2007; Schlermelleh-Engel et al. 2003, Vandenberg, 2006).

Absolute Fit Index

The purpose of an absolute fit index is to determine how well a previously determined (i.e., expected) model fits the observed data (McDonald & Ho, 2002). In the case of this study, the absolute fit index includes both the χ^2 test and the Root Mean Square Error of Approximation (RMSEA). The RMSEA is used both descriptively and inferentially to determine fit (Peugh & Feldon, 2020). The RMSEA is a standardized measure not bound to the scale of the measured latent variables. The RMSEA assesses the lack of a model fit without a comparison of the other models by taking into account the model complexity relative to the amount of data. The RMSEA test allows for hypothesis testing (Schermelleh-Engel et al., 2003).

Specifically, the RMSEA point estimate is compared to a cut-off point. The cut-off is < 0.05 for good model fit and < 0.08 for acceptable model fit (Awang, 2012; Hair et al., 2010, Kliem et al., 2017). In terms of hypothesis testing, the critical point relates to a specific significance level used to reject the null hypothesis. I rejected the null hypothesis with an expected value beyond the expected cutoff value. In addition, I inspected and reported the 90% confidence interval of the RMSEA, with an acceptable range from .05 for the low end and .08 for the high end of the interval (Hu & Bentler, 1999)

The third absolute fit index in this study is the Standardized Root Mean Residual (SRMR). The SRMR is a measure of fit of the covariance in the model. Precisely, the SRMR measures the standardized difference between a predicted correlation and the observed correlation. A value of 0.00 is an exact fit, .01-.08 is an acceptable fit, and higher than .08 is a poor fit (Hu & Bentler, 1999). I rejected the null hypotheses with values beyond the expected value in the relative fit index.

Relative Fit Index

The purpose of a relative fit index is to compare a estimated model with a null or independence model.. The first relative fit index in this research is The Comparative Fit Index (CFI). Tenenhuasu et al. (2004) proposed the CFI index to globally fit in a partial least squares model. The CFI represents the "amount of variance and covariance matrix" accounted for by the model; the index ranges from 0.0 (a lack of fit) to 1.0 (exact good fit) (p. 33). A value of .95-.99 is a good model fit; .95-.90 is an acceptable fit, and less than 0.90 is a poor fit (Kliem et al., 2017).

The second relative fit index is the Tucker Lewis Index (TLI). The Tucker Lewis Index is also known as the non-normed fit index (NNFI; Bentler & Bonett, 1980) used in covariances and linear mean modeling. Values less than 0.9 is a poor fit; values greater than 0.9 is an acceptable fit (Hu & Bentler, 1999).

Model Evaluation

Fit indices of RMSEA (≤.06); RMSEA 90% confidence interval (90% C.I.) smaller or equal to .05 and the upper value less than or equal to .08; SRMR (<.08); CFI (≥.90); TLI (>.90). In addition to fit criteria, standardized residuals greater than 2.58 (at a nominal alpha level of $p<.01$) will be considered outside the appropriate range.

Missing Data

In this research, I addressed missing observations first through considering whether the data missing was completely at random, which is called Missing Completely at Random (MCAR), missing at random (MAR) or missing not at random (MNAR) (Li & Lomax, 2017). I investigated whether the missing data was MCAR by running Little's Missing Completely at Random Test in R-software. If the missing data was completely at random, the researcher addressed them using a Missing Data Treatment (MDT). The MDT used in this study was the data imputation function in the SPSS software. Data imputation is a method to estimate missing data for parameters by determining the maximizing likelihood function based on the sample data (Little, 2013). Data imputation is favored to just applying the mean values as data imputation generates smaller parameter estimate bias, is more efficient, and has lower and more consistent rates of model rejection (Li & Lomax, 2017). In the event the amount of data missing in this study is less than 5%, a single imputation will be used.

Ethical Considerations

The University of Houston requires compliance with the ethical standards of human experimentation. First, voluntary participation of respondents is necessary. Furthermore, participants are informed prior to consent that they have the right to withdraw at any point if they desire. Second, respondents required to participate by informed consent. Informed consent requires researchers to provide sufficient information and proper assurances about taking part in the study to allow participants to fully understand the implications and decide if they wish to give their consent, without interference or coercion. Third, the use of language, which is offensive, discriminative, or any other way unacceptable, is avoided in the development of the questionnaire and informed consent. Fourth, privacy and anonymity considerations are the primary concern when handling data during the study, including storing information on a cloud that requires a password and publishing the results collectively to ensure anonymity. Fifth, the acknowledgement of work of other authors and researchers used in the dissertation is required through the use of the APA referencing system according to the University of Houston Handbook. Sixth, researchers are expected to hold the highest level of objectivity in the analysis and conclusion throughout the research. And finally, researchers are expected to follow the University of Houston's guidelines of research throughout the entire study.

Limitations

The first limitation regarding the results of my study relates to the study design. As this is a study that utilizes latent variables, there is concern about the measurements made in the study reflecting the actual variables. Previous research has equated Mathematical Attribution of Expectancy with both Mathematical Self-Concept and Mathematical Self-Efficacy (Skaalvik & Skaalvik, 2006; Swars et al, 2006). However, a limitation of this research includes the need for a third indicator for Mathematical Attribution of Expectancy to improve the measurement of the latent variable Mathematical Attribution of Expectancy. Additional limitations include missing data in the experiment, which were accounted for through an imputation rather than actual responses, which would influence the validity of the study.

In addition to assumptions of latent variables, there are other limitations of my study design. Specifically, my study is a cross-sectional and not a longitudinal study. Likewise, I addressed missing data by taking averages. The study may have produced different results with complete responses to the questions. Due to the study being a correlation, the study cannot attribute causality to the factors investigated. The generalization of the population through low response rates may misrepresent grade-level choices.

Another limitation of my study includes the number of items. The survey constructed in this study utilized three instruments to develop the survey, leaving 38 items to indicate the six first level latent variables. Specific research indicates that an increase of items per factor can affect goodness-of-fit indexes and negatively influence statistical power (Wang, 2015, p. 437; Xia & Yang, 2019). Additionally, the combination of multiple surveys to create multiple second order latent variables creating model complexity which would impact the χ^2 test statistic.

Beyond that, due to low response rates, I was not able to collect enough data to run a desired analysis. Specifically, I did not have a large enough sample, which limited my analysis of all race/ethnicity groups. In this study I had to break down the race/ethnicity groups investigated into Caucausian/White and Minority/Not-Asian. Furthermore, I made the assumption that schools place pre-service teachers at a level the presevice teacher anticipates to teach. Teachers may not be placed at the grade level they antcipate and the individuals of this study may not reflect the actual population of practing teachers. Next, pre-service teachers sampled were at a different stage of their training. Individuals at the beginning of the training may not finish the training or may change their decision at which grade level to teach. Finally, as different teaching levels and certifications have different program requirements, preservice teacher goals and perceptions of the job may be influenced by the teaching program directly.

Chapter 4

Results

Overview of the Chapter

The following chapter presents the results from the current study. A detailed depiction of the study participants is provided in the first section. The following section reports the results of the data screening for the analysis. The third section reports the results of the CFA through the evaluation of goodness of fit indices, model specification, χ^2 test significance, and the interpretation of parameter estimates of each model. The chapter concludes with the results from the models that fit appropriately.

Data Screening

First, I screened raw data to evaluate whether the underlying assumptions of CFA were tenable. Specifically, I evaluated descriptive statistics such as means, standard deviations, kurtosis and skewness and correlation coefficients to ensure that the assumptions underlying CFA were met. I utilized a robust maximum likelihood estimator (MLR) in this study as certain indicators such as q_1, q_2, q_3, q_4, q_5, and q_6 were identified as non-normally distributed with the skewness values above two.

Following the descriptive statistics analysis, I identified data outliers with SPSS through an examination of the histograms and boxplots. An outlier is identified as a value greater than 2.5 standard deviations (Brase & Brase, 2011) and therefore, I removed all values with a standard deviation greater than 2.5. First, I identified 34 data points as outliers, and I removed them from the sample.

Next, I tested the data with a Mahalanobis d-square on SPSS. I identified 21 responses as having a Mahalanobis d-squared distance more than 75. I removed these 21 responses from the analysis sample.

I further analyzed the data after the data outliers were removed. The descriptive statistics for the remaining survey items are reported in Table D2. An analysis of the correlation coefficients included an analysis of the effect size of the Pearson Coefficients.

The most significant data in Table D2 is the skewness and kurtosis. The values were compared with standard values. Traditional normality tests include a z-score for kurtosis and skewness within a value of ±1.96 (Corrado & Su, 1997; Wright & Herrington, 2011), or the Shapiro-Wilk test and Kolmogorov-Smirnov test. The kurtosis/skewness z-score is most accurate with smaller samples (N<50), and the Shapiro-Wilk test and Kolmogorov-Smirnov test are most appropriate for medium sized samples between 50 and 300. In the sample used in this study, the most appropriate measure of normality is an absolute skewness score less than two and an absolute kurtosis less than seven (West et al., 1995). In Table 4 all values are found within these accepted ranges except for General Utility Skewness and Kurtosis. GU1, GU2, GU3, GU4, GU5, GU6 and GU7 had Skewness and Kurtosis values outside the accepted boundaries. Table 3 summarizes the relative size coefficients and the strength of association (Cohen, 1992). An inspection of the effect sizes of the correlations between items reveals a large effect size between items I4 and I2; I3 and I4; I2 and I5; I3 and I5; GU2 and GU3; NFHAI1 and NFHAI2; PC1 and PC2; PC1 and PC3; PC2 and PC3.

Table 3

Relative Size Coefficients

	Relative Size Coefficient	
Strength of Association	Positive	Negative
Small	.1 to .3	-.1 to -.3
Medium	.3 to .5	-.3 to-0.5
Large	.5 to 1.0	-.5 to -1.0

(Cohen, 1992)

Table D3 lists the correlation coefficients, effect sizes, relative sizes and covariance between items. Most of the values of the correlation coefficients, effect sizes, relative size and covariances fall within the accepted range (West et al., 1995). The values of the relative size coefficients are interpreted using the accepted values found in Table 3 (Cohen, 1992). *Missing Data*

All participants failing to respond to at least 50% of the survey were removed from the analysis. In this study, responses from 48 participants were removed. These 48 participants started the survey but did not answer any of the item questions. As such, these samples were inappropriate for an imputation method and were removed.

Next, missing data were examined in SPSS version 26 to ensure missing data was not Missing at Random (MAR). The data were analyzed using Little's MCAR test Analysis of the data provided the following results: χ^2 = 939.283, df = 935, p-value 0.454. The missing data was determined to be Missing Completely at Random (MCAR) based on Little's MCAR test. When considering missing values in missing value imputations two necessary considerations are missing power, which occurs with increased imputations, and the adequate number of imputations required for missing data. According to Graham et al. (2007), 4-10 imputations were appropriate for this study. In this study missing values were imputed using the SPSS imputation function utilizing the Monte Carlo Method and a maximum of 10 imputations.

I administered the survey to 356 preservice teachers. A reference for a detailed description on the demographics for gender, ethnicity, age, and certification types is provided in Table 4 below.

Table 4

Demographic Data

Demographic Value		Frequency %
Gender	Male	11.9
	Female	86.7
	Other	1.4
Race		
	White/Non-Hispanic	30.3
	American Indian/Alaska Native	0.3
	Asian	15.6
	Black or African American	5.9
	Latino/Hispanic	45.3
	Other	3.1
Certification Type		
	Mathematics	23.8
	Non-Mathematics	76.8
Grade Level Choice		
	Early Primary (K-2)	36.3
	Upper Primary (3-5)	20.4
	Middle School (6-8)	17.6
	Secondary (9-12)	26.6

The study was anonymous and the personal information about students was not gathered. As a result, the identifying information for each university in the data is not available. The Qualtrics study removed all candidates stating they were not at least 18 years old or an education major. The range of ages was 15 years, with the youngest participant reported being 18 years old and the oldest reported being 33 years old.

Hypothesis Evaluation

In order to test the study's hypotheses, 10 models were constructed. Model 1.1 consists of a first order CFA model of six latent factors (Math Self Concept

Math Self Efficacy, General Utility, Need for High Achievement, Interest, Cost) of all preservice teachers to serve as a comparison model. Models 1.2, 2, 3, 4, 5, 6, 7, 8, and 9 are second order CFA models consisting of six first-order latent factor factors (Math Self Concept Math Self Efficacy, General Utility, Need for High Achievement, Interest, Cost) hypothesized to load on two second-order latent factors (Attribution of Expectancy and Math Task Value). The overall description of the study models is provided in Table 5.

Table 5

Description of Models

Model	N	Description	Order	Latent Variables	Grades
1.1	356	All Preservice Teachers	1st	6	K-12
1.2	356	All Preservice Teachers	2nd	8	K-12
2	200	All Primary Preservice Teachers	2nd	8	K-5
3	306	All Female Preservice Teachers	2nd	8	K-12
4	171	All Minority/Not Asian Female Preservice Teachers	2nd	8	K-12
5	188	Female All Primary Preservice Teachers	2nd	8	K-5
6	107	All Caucasian/White Preservice Teachers	2nd	8	K-12
7	118	All Secondary Female Preservice Teachers	2nd	8	9-12
8	155	All Secondary/Middle School Preservice Teachers	2nd	8	6-12
9	128	All Early Primary Preservice Teachers	2nd	8	K-2
10	193	All Minority/Not Asian Preservice Teachers	2nd	8	K-12

After addressing screening issues, an analysis of the data using R and R-studio and utilizing a robust maximum likelihood function was conducted in the Lavaan package 0.6-5 (Rosseel, 2012). The following section reports the fitted CFA solution and SEM solution for each model through a presentation of associated goodness of fit values, fit indices, statistical significance, and the number of freely estimated parameters. As noted in Chapter 3, acceptable model fit is defined through the following criteria: Fit indices of RMSEA ($\leq .06$); RMSEA 90% confidence interval (90% C.I.) smaller or equal to .05 and the upper value less than or equal to .08; SRMR ($<.08$); CFI ($\geq .90$); TLI ($>.90$). In addition to fit criteria, standardized residuals greater than 2.58 (at a nominal alpha level of $p<.01$) were considered outside the appropriate range.

Hypothesis 1.

Hypothesis 1 states: Items 1-6 are indicators for the first-order latent variables Mathematical Self-Efficacy; items 7-10 are indicators for the first-order latent variables Mathematical Self-Concept; items 11-17 are indicators of the first-order latent indicator Interest; questions 18- 24 are indicators of the first-order latent variable General Utility; items 25-31 are indicators for the first-order latent variable Need for High Achievement; items 32-38 are indicators of the first-order latent variable Personal Cost.

In order to test the first hypothesis, CFA analyses were conducted on all models. All associated model data were reported with each model's goodness of fit data reported individually. The following section provides the outcome of the model analyses.

Model 1.1

Model 1.1 is a first-order six factor CFA model consisting six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, and General Utility. Model 1.1 consists of the entire population of preservice teachers. Model 1.1 serves as an alternative model for comparison. The goodness of fit indices is reported in Table 6.

Table 6

CFI Fit Statistics for Model 1.1 (N= 356)

Model	1.1
χ^2_{SB}	1380.84
p	<0.001
df	650
RMSEA	0.056
90% C.I.	[.054, .063]
SRMR	0.064
CFI	0.901
TLI	0.907

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = Tucker Lewis index.

According to the goodness of fit indices, the model is an acceptable model fit. The means, standard deviations and intercorrelations for all latent variables for Model 1.1 are reported in Table 7.

Table 7

Means, Standard Deviations, and Intercorrelations among All Latent Variables for Model 1.1

Variable	1	2	3	4	5	6
1. Efficacy	1					
2. Concept	0.572	1				
3. Interest	0.47	0.79	1			
4. Utility	-0.115	-0.07	-0.085	1		
5. Achievement	0.197	0.505	0.434	0.023	1	
6. Cost	-0.51	-0.706	-0.538	0.027	0.049	1
Mean	0.1228	0.2182	0.2142	-0.044	0.2416	-0.3356
SD	0.39619	0.54251	0.46917	0.05819	0.1966	0.3124

Note: Efficacy = Attribution of Expectancy; Concept = Math Self Concept; Interest = Interest; Utility = General Utility

Model 1.2

Model 1.2 is a second-order CFA model consisting of eight latent factors. The six first-order latent factors include Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two second-order latent factors Mathematical Attribution of Expectancy and Mathematical Task value. Model 1.2 consists of the entire sample of preservice teachers. The goodness of fit indices is reported in Table 8.

Table 8

CFI Fit Statistics for Model 1.2

Model	1.2
N	356
χ^2_{SB}	1027.62
p	<0.001
df	520
RMSEA	0.055
90% C.I.	[.05, .059]
SRMR	0.068
CFI	0.933
TLI	0.928

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indices indicate Model 1.2 is currently an acceptable fit. Additionally, the chi squared analysis for this model is significant. The correlation of Attribution of Expectancy and Task Value has a 1.059 unstandardized estimate. The means, standard deviations and intercorrelations among all latent variables for Model 1.2 are reported in Table 9.

Table 9

Means, Standard Deviations, and Intercorrelations among All Latent Variables for Model 1.2

Variable	1	2	3	4	5	6	7	8
1. Efficacy	1							
2. Concept	0.573	1						
3. Interest	0.487	0.790	1					
4. Utility	-0.056	-0.091	-0.069	1				
5. Achievement	0.302	0.490	0.372	-0.043	1			
6. Cost	-0.440	-0.713	-0.541	0.062	-0.335	1		
7. AOE	0.594	0.964	0.820	-0.094	0.508	-0.739	1	
8.Task	0.629	1.020	0.774	-0.089	0.480	-0.698	1.059	1
Mean	0.298	0.433	0.376	-0.054	0.253	-0.332	0.445	0.454
SD	0.373	0.581	0.475	0.051	0.298	0.443	0.598	0.591

Note: Efficacy = Attribution of Expectancy; Concept = Math Self Concept; Interest = Interest; Utility = General Utility; Achievement = Need for High Achievement; Cost = Personal Cost; AOE = Attribution of Expectancy; Task = Task Value; all $p < 0.05$

Model 2

Model 2 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 2 consists of the entire population of primary preservice teachers. The goodness of fit indices for Model 2 are reported in Table 10.

Table 10

CFI Fit Statistics for Model 2

Model	2
N	200
χ^2_{SB}	1151.78
P	<0.001
df	658
RMSEA	0.064
90% CI	[.058, .07]
SRMR	0.076
CFI	0.897
TLI	0.89

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indices indicate Model 2 is a not yet acceptable fit. Due to an CFI <.90, I determined this model is not an acceptable fit. The correlation of Attribution of Expectancy and Task Value has a Haywood Case with a standardized estimate of 1.072.

Model 3

Model 3 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 3 consists of the entire population of all preservice teachers. The goodness of fit indices for Model 3 are in Table 11.

Table 11

CFI Fit Statistics for Model 3

Model	3
N	306
χ^2_{SB}	1332.64
p	<0.001
df	658
RMSEA	0.06
90% CI	[.056, .065]
SRMR	0.075
CFI	0.909
TLI	0.903

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% CI = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indices indicate the model for all female primary teachers is an acceptable fit. The results show a significant chi-squared for this model. Additionally, the model has standardized variances of second-order, exogenous latent factors for Attribution of Expectancy with a standardize estimate of 1 and Math Task Value with a standardized estimate of 1, and a covariance for Attribution of Expectancy and Math Task Value with an unstandardized value of 1.057. The means, standard deviations and Intercorrelations among all latent variables for Model 3 are presented in Table 12.

Table 12

The Means, Standard Deviations and Intercorrelations among All Latent Variables for Model 3

Variable	1	2	3	4	5	6	7	8
1. Efficacy	1							
2. Concept	0.542	1						
3. Interest	0.482	0.794	1					
4. Utility	-0.097	-0.160	-0.128	1				
5. Achievement	0.317	0.523	0.417	-0.084	1			
6. Cost	-0.443	-0.729	-0.581	0.117	-0.382	1		
7. AOE	0.574	0.994	0.841	-0.170	0.554	-0.772	1	
8.Task	0.606	0.998	0.796	-0.161	0.524	-0.730	1.057	1
Mean	0.283	0.423	0.374	-0.098	0.267	-0.337	0.440	0.441
SD	0.372	0.596	0.500	0.092	0.335	0.472	0.623	0.608

Note: Efficacy = Attribution of Expectancy; Concept = Math Self Concept; Interest = Interest; Utility = General Utility; Achievement = Need for High Achievement; Cost = Personal Cost; AOE = Attribution of Expectancy; Task = Task Value; all $p < 0.05$

Model 4

Model 4 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 4 includes a sample of all Minority/non-Asian female preservice teachers. The goodness of fit indices for Model 4 are reported in Table 13.

Table 13

CFI Fit Statistics for Model 4

Model	4
N	171
χ^2_{SB}	1090.82
p	<0.001
df	658
RMSEA	0.06
90% C.I.	[.054, .066]
SRMR	0.075
CFI	0.912
TLI	0.906

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% CI = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indicates Model 4 is an acceptable fit. Heywood cases exist for Attribution of Expectancy of 1 and Math Task Value of 1, and a standardized covariance of 1.038. Additionally, the Chi Squared statistic is significant for this model.

Model 5

Model 5 is a second-order CFA Model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 5 consists of female all primary preservice teachers. The goodness of fit indices for Model 5 are reported in Table 14.

Table 14

CFI Fit Statistics for Model 5

Model	5
N	188
χ^2_{SB}	1129.42
p	<0.001
df	658
RMSEA	0.064
90% C.I.	[.058, .07]
SRMR	0.076
CFI	0.879
TLI	0.871

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indices indicate Model 5 is a not acceptable fit. Due to a CFI <.90 and TLI < .90, I found this model not to be an acceptable fit.

Model 6

Model 6 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 6 includes a sample of all Caucasian/White preservice teachers.

Model 6 was found to be such a poor fit that Lavaan could not run the CFA due to no model convergence, and as such, the model is considered a not yet acceptable fit. The inability to run the model in Lavaan results in the researcher not conducting an examination of the parameter estimates of Model 6.

Model 7

Model 7 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 7 includes a sample of all female secondary preservice teachers. The results of the goodness of fit indices indicate Model 7 does not show acceptable fit to the data. The estimates for Model 7 are reported in Table 15 below.

Table 15

CFI Fit Statistics for Model 7

Model	7
N	118
χ^2_{SB}	1100.34
p	<0.001
df	658
RMSEA	0.079
90% C.I.	[.071, .087]
SRMR	0.107
CFI	0.841
TLI	0.794

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The results of the goodness of fit indices indicate Model 7 is a not yet acceptable fit. As the reported CFI <.90 and SRMR >.08 I rejected this model.

Model 8

Model 8 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task value. Model 8 includes the entire population of all secondary/middle school preservice teachers. The goodness of fit indices for Model 8 are reported in Table 16.

Table 16

CFI Fit Statistics for Model 8

Model	8
N	155
χ^2_{SB}	1106.74
p	<0.001
df	658
RMSEA	0.07
90% C.I.	[.062, .077]
SRMR	0.101
CFI	0.852
TLI	0.864

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

The goodness of fit indices indicates Model 8 is not an acceptable fit. Due to an RMSEA >.06 I rejected this model. Heywood cases exist for this model with a standardized estimate of General Utility of 1; Attribution of Expectancy a standardized estimate of 1; Math Task Value a standardized estimate of 1. A Heywood case exist for the covariance of Attribution of Expectancy and Task Value with a value of 1.069.

Model 9

Model 9 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task

Value. The results of the goodness of fit indices indicate Model 9 is a not yet acceptable fit. The goodness of fit indices for Model 9 are reported in Table 17.

Table 17

CFI Fit Statistics for Model 9

Model	9
N	
χ^2_{SB}	1037.14
p	<0.001
df	658
RMSEA	0.07
90% C.I.	[.061, .077]
SRMR	0.089
CFI	0.871
TLI	0.863

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

Due to a CFI >0.06, SRMR <.90 I rejected this model.

Model 10

Model 10 is a second-order CFA model consisting of eight latent factors. The six latent variables of Math Self Efficacy, Math Concept, Interest, General Utility, Need for High Achievement, General Utility are indicators of the two latent variables Mathematical Attribution of Expectancy and Mathematical Task Value. The goodness of fit indices for Model 10 are reported in Table 18.

Table 18

CFI Fit Statistics for Model 10

Model	10
N	193
χ^2_{SB}	1090.82
p	<0.001
df	658
RMSEA	0.060
90% C.I.	[.054, .066]
SRMR	0.075
CFI	0.912
TLI	0.906

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of analysis; 90% C.I. = 90% confidence interval of RMSEA; CFI = comparative fit index; SRMR = standardized root mean square residual; TLI = tucker lewis index.

Model 10 includes the entire population of Minority/non-Asian preservice teachers. As the CFI fit statistics for this model is within the acceptable range, this model is determined to be an acceptable fit. Additionally, the model has standardized variances of second-order, exogenous latent factors for Attribution of Expectancy with a standardize estimate of 1 and Math Task Value with a standardized estimate of 1, and a covariance for Attribution of Expectancy and Math Task Value with an unstandardized value of 1.038. Additionally, the Chi-squared statistic is significant for this model.

Hypothesis 1 Summary

Hypothesis 1 states: *Items 1-6 are indicators for the first-order latent variables Mathematical Self-Efficacy; items 7-10 are indicators for the first-order latent variables Mathematical Self-Concept; items 11-17 are indicators of the first-order latent indicator Interest; questions 18- 24 are indicators of the first-order latent variable General Utility; items 25-31 are indicators for the first-*

order latent variable Need for High Achievement; items 32-38 are indicators of the first-order latent variable Personal Cost.

In the CFA analysis, Model 1.1, 1.2, Model 3, Model 4, Model 10, were deemed acceptable model fits. The other models failed the analysis of both the CFA and the SEM fit. A summary of the Robust Maximum Likelihood CFA Fit for all models is reported in Table 19. The measurement models indicate all indicators are positive and load for the first order latent variables.

Table 19

Robust Maximum Likelihood CFA Fit Statistics

					Absolute Fit Indices			Comparative Fit Indices	
Model	**N**	**p**	**χ^2_{SB}**	**df**	**RMSEA**	**90% C.I.**	**SRMR**	**CFI**	**TLI**
1.1*	356	<0.001	1380.84	650	0.056	[.054, .063]	0.064	0.901	0.907
1.2*	356	<0.001	1027.62	520	0.055	[.05, .059]	0.068	0.933	0.928
2	200	<0.001	1151.78	658	0.064	[.058, .070]	0.076	0.897	0.89
3*	306	<0.001	1332.64	658	0.06	[.056, .065]	0.075	0.909	0.903
4*	171	<0.001	1090.82	658	0.06	[0.054, .066]	0.075	0.912	0.906
5	188	<0.001	1129.42	658	0.064	[.058, .070]	0.076	0.879	0.871
6	107	NA	NA	NA	NA	NA	NA	NA	NA
7	118	<0.001	1100.34	658	0.079	[.071, .087]	0.107	0.841	0.794
8	155	<0.001	1106.74	658	0.7	[.062, .077]	0.101	0.852	0.864
9	128	<0.001	1037.14	658	0.07	[.061, .077]	0.089	0.871	0.863
10*	193	<0.001	1090.82	658	0.06	[.054, .066]	0.075	0.912	0.906

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval SRMR = Standardized Root Mean Square Residual; CFI = Comparative Fit Index; TLI = Tucker Lewis Index.
*=model pass

In the analysis of the SEM models, Model 1.1, 1.2, Model 3, Model 4, Model 10, were deemed acceptable model fits. summary of the Robust Maximum Likelihood SEM Fit for all models is reported in Table 20. The measurement models show all indicators are positive and load for the first order latent variables. The SEM fit statistic demonstrates whether the respective latent factor is a significant predictor for the outcome variable (Holtzman & Vezzu, 2011).

Table 20

Robust Maximum Likelihood SEM Fit Statistics

					Absolute Fit Indices			Comparative Fit Indices	
Model	**N**	**p**	**χ^2_{SB}**	**df**	**RMSEA**	**90% C.I.**	**SRMR**	**CFI**	**TLI**
1.1*	356	<0.001	1380.84	650	0.059	[.054, .063]	0.066	0.914	0.907
1.2*	356	<0.001	1027.62	520	0.055	[.050, .059]	0.078	0.933	0.928
2	200	<0.001	1129.42	658	0.064	[.058, .070]	0.076	0.897	0.89
3*	306	<0.001	1332.64	658	0.06	[.056, .065]	0.076	0.909	0.903
4*	171	<0.001	1090.82	658	0.06	[.054, .066]	0.077	0.912	0.906
5	188	<0.001	1129.42	658	0.064	[.058, .070]	0.078	0.897	0.89
6	107	NA	NA	NA	NA	NA	NA	NA	NA
7	118	<0.001	820.326	520	0.073	[.071, .087]	0.096	0.878	0.868
8	155	<0.001	1106.74	658	0.07	[.062, .077]	0.106	0.872	0.864
9	128	<0.001	1037.14	658	0.07	[.061, .077]	0.091	0.871	0.863
10*	193	<0.001	1090.82	658	0.06	[.012, .060]	0.077	0.912	0.906

Note: χ^2 = chi square; df = degrees of freedom; RMSEA = root mean square error of approximation; 90% CI = RMSEA 90% at confidence interval; SRMR = standardized root mean square residual; CFI = comparative fit index; TLI = tucker lewis index.
*=model pass

Figure 5 represents the Measurement Model for Model 1.1. The figure shows most loadings are positive and in the expected direction except for Math Efficacy and Math Self-Concept which shows a covariance of -.062. In Figure 5 Math Self Efficacy is coded as efficacy; Math Self-Concept is coded as concept; Interest is coded as interest; General Utility is coded as utility; Need for High Achievement is coded achievement; Personal Cost is coded cost. The model was generated in TidySEM R package Van Lissa (2019).

Figure 5

Measurement Model for Model 1.1

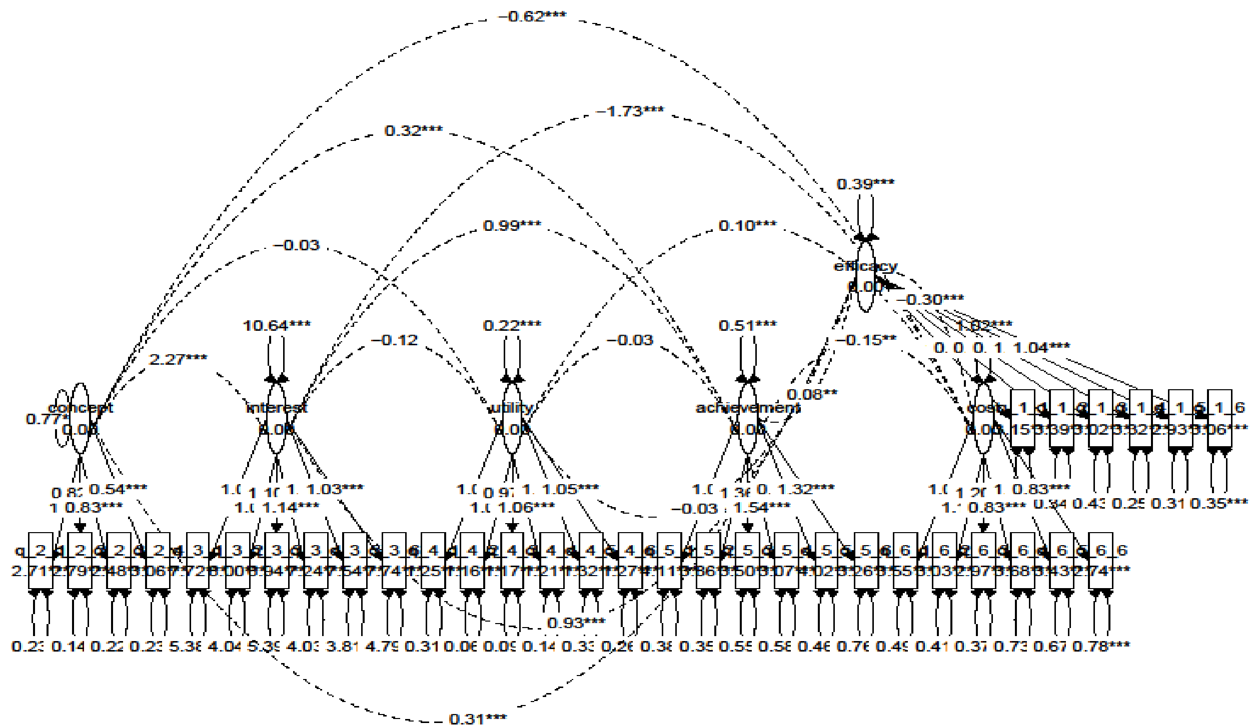


Figure 6 represents the Measurement Model for Model 1.2. The figure shows most loadings are positive and in the expected direction except for Cost and Task Value which shows a covariance of -.28. In Figure 5 Math Self Efficacy is coded as efficacy; Math Self-Concept is coded as concept; Interest is coded as interest; General Utility is coded as utility; Need for High Achievement is coded achievement; Personal Cost is coded cost. The figure was generated in TidySEM R package Van Lissa (2019).

Figure 6

Measurement Model for Model 1.2 (Van Lissa, 2019)

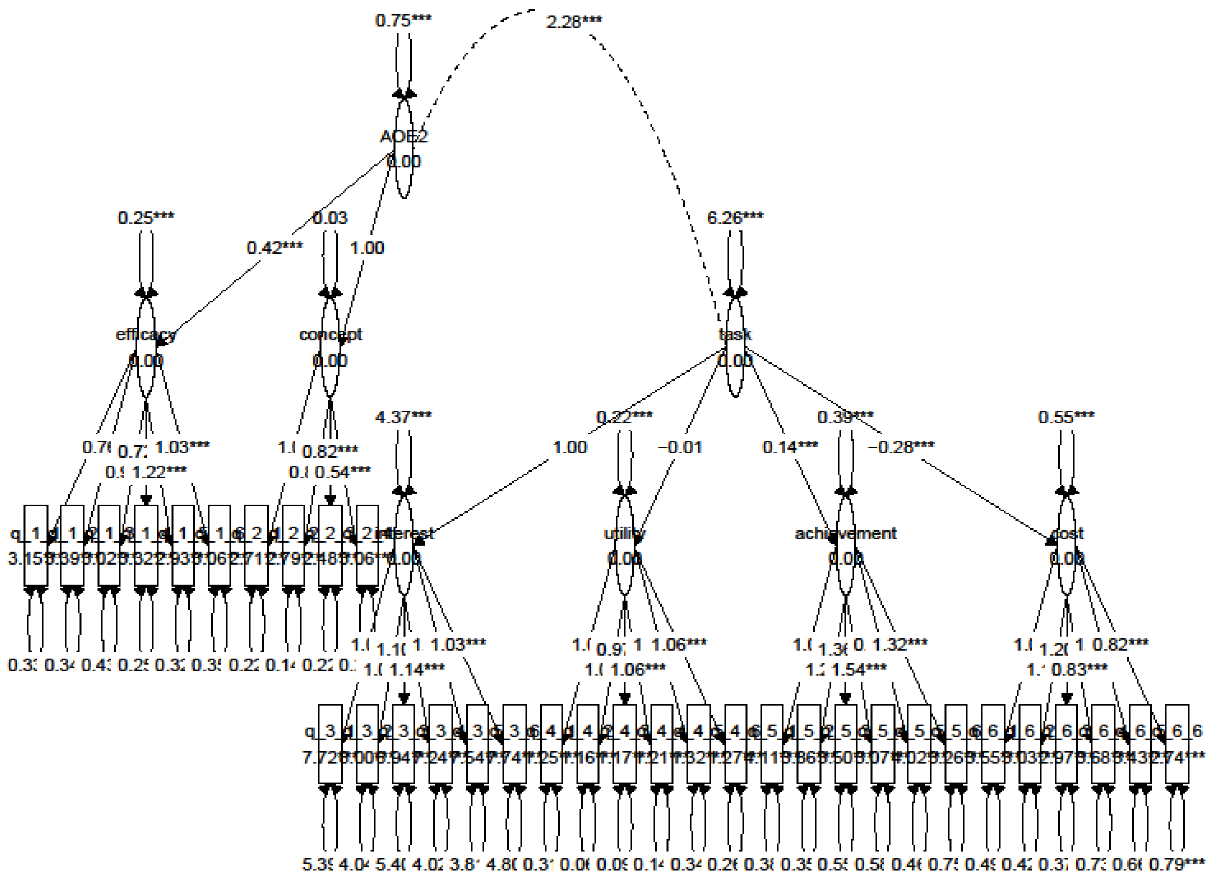


Figure 7 represents the Measurement Model for Model 1.2. The figure shows most loadings are positive and in the expected direction except for Cost and Task Value which shows a covariance of -.28. In Figure 5 Math Self Efficacy is coded as efficacy; Math Self-Concept is coded as concept; Interest is coded as interest; General Utility is coded as utility; Need for High Achievement is coded achievement; Personal Cost is coded cost. The figure was generated in TidySEM R package Van Lissa (2019).

Figure 7

Measurement Model for Model 3 (Van Lissa, 2019)

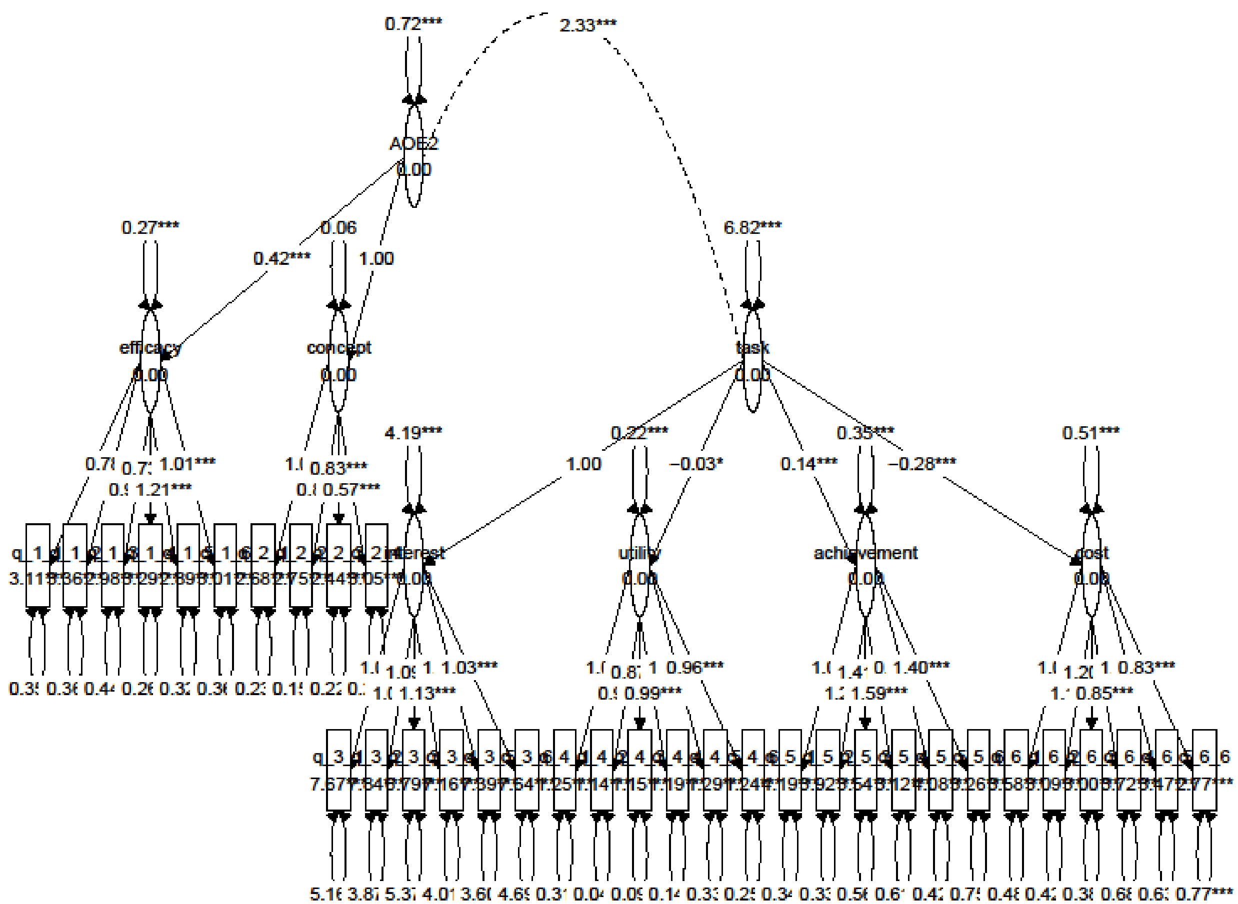


Figure 8 represents the Measurement Model for Model 1.2. The figure shows most loadings are positive and in the expected direction except for Cost and Task Value which shows a covariance of -.27. In Figure 5 Math Self Efficacy is coded as efficacy; Math Self-Concept is coded as concept; Interest is coded as interest; General Utility is coded as utility; Need for High Achievement is coded achievement; Personal Cost is coded cost. The figure was generated in TidySEM R package Van Lissa (2019).

Figure 8

Measurement Model for Model 4 (Van Lissa, 2019)

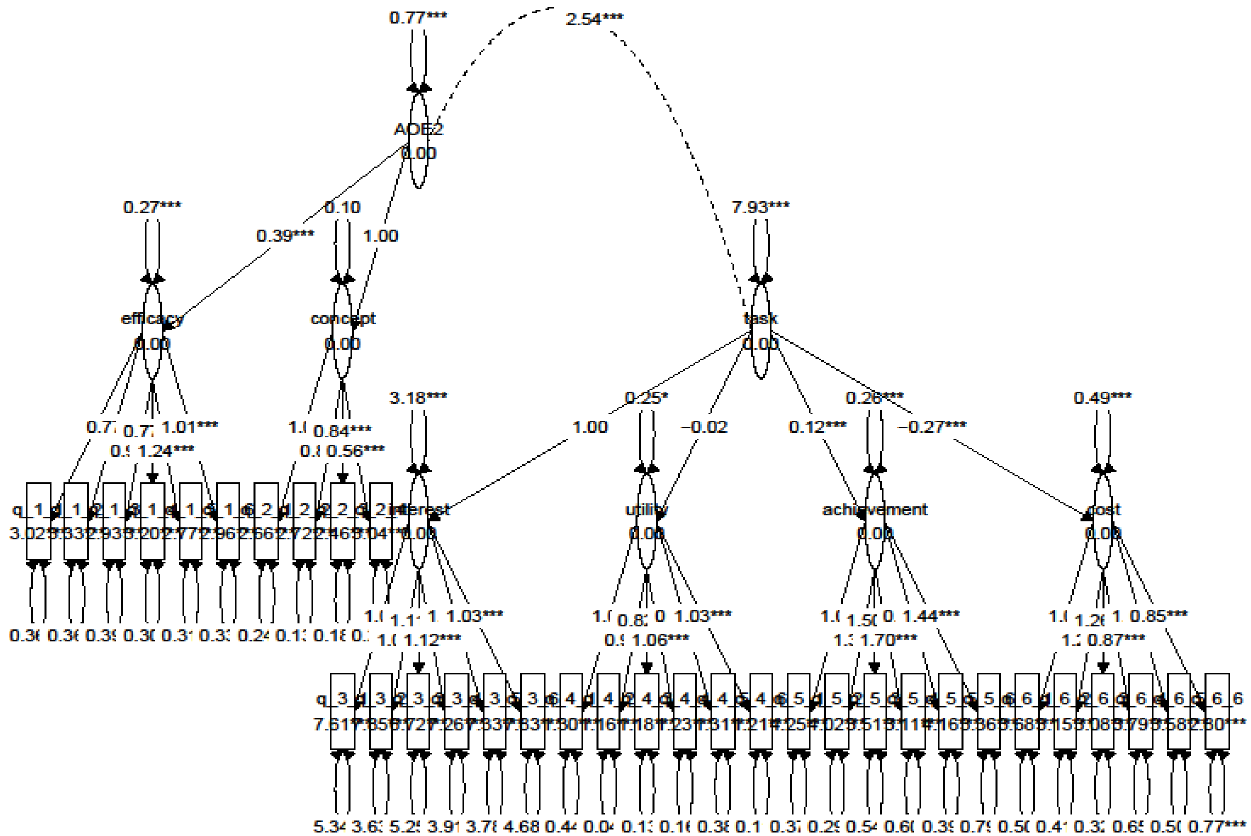
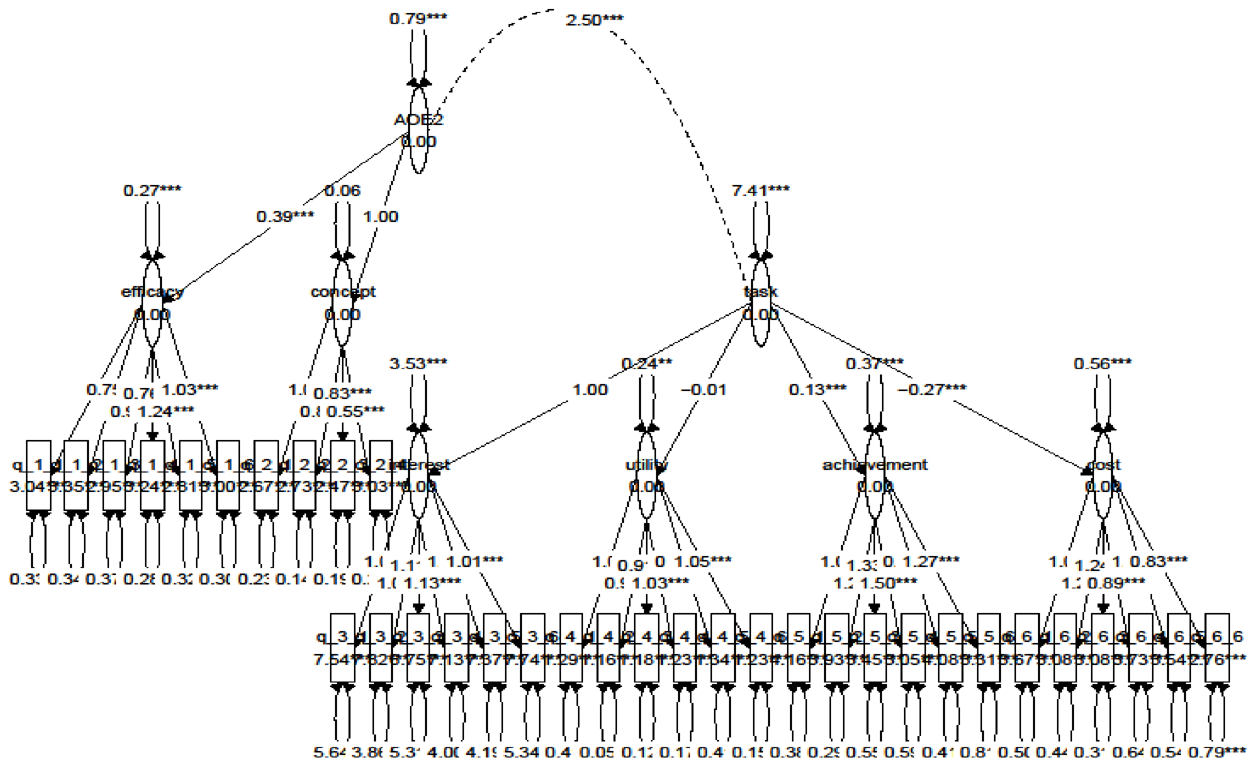


Figure 9 represents the Measurement Model for Model 10. The figure shows most loadings are positive and in the expected direction except for Cost and Task Value which shows a covariance of -.27 and Utility and Task Value with a value of -.01. In Figure 5 Math Self Efficacy is coded as efficacy; Math Self-Concept is coded as concept; Interest is coded as interest; General Utility is coded as utility; Need for High Achievement is coded achievement; Personal Cost is coded cost. The figure was generated in TidySEM R package Van Lissa (2019).

Figure 9

Measurement Model for Model 10 (Van Lissa, 2019)



After an analysis of the data, most of the data is within the range and direction I expected. Overall, I found Models 1.1, 1.2, 3, 4, and 10 were acceptable fits and I have rejected the null hypothesis.

Hypothesis 2

Hypotheses 2 states**:** *Mathematical Self-Efficacy has a positive effect on Mathematical Attribution of Expectancy; Mathematical Self-Concept has a positive effect on Mathematical Attribution of Expectancy, Interest has a positive effect on Mathematical Task Values; General Utility has a positive effect on Mathematical Task Values; Need for High Achievement has a positive effect on Mathematical Task Values; Personal Cost has a positive effect on Mathematical Task Values.*

In the CFA analysis, I deemed Model 1.1, 1.2, Model 3, Model 4, Model 10, to have acceptable model fit. The other models failed both the CFA and the SEM analyses. In an analysis of the models, Utility and Cost I found to be negatively influencing Task Value for all models. Models 1.2, 3 and 4 had a standardized covariance between Attribution of Expectancy and Task Value greater than one indicating a Heywood case. The misspecification resulting in the Heywood case may be due to the negative loadings of utility and cost. As such, I cannot reject the null hypotheses for these factors.

Hypothesis 3

Hypothesis 3 states: *The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical*

Task Values are dependent on gender, such that the effect of Mathematical Attribution of Expectancy and Mathematical Task Value is stronger when the gender is female.

In the analysis, I was unable to analyze the Model of overall male due to small sample size. Accordingly, the ability to test Hypothesis 3 is limited. The only models that passed a CFA model analysis and SEM model analysis were Model 1.1 (All Preservice Teachers); Model 1.2 (All Preservice Teachers); Model 3 (All Female Preservice Teachers), Model 4 (All Minority/Not Asian Female Preservice Teachers); Model 10 (All Minority/Not Asian Preservice Teachers). As Model 1.1, and Model 1.2 were similar to Model 3 with only a difference in gender, all Models passing show no difference in gender. Additionally, as Models 4 and Models 10 are the same population with only a difference in pre-service teacher gender, both Models passing indicates no differences in gender. As such I cannot reject the null hypothesis.

Hypothesis 4

Hypothesis 4 states: *The effect of Mathematical Self-Efficacy and Mathematical Self-Concept on Mathematical attribution of Expectancy; Interest, General Utility, Need for High Achievement, Personal Cost on Mathematical Task Values are dependent on ethnicity, such that the effect of Mathematical Attribution of Expectancy and Mathematical Task Value is stronger when the ethnicity is Caucasian/White*.

In the analysis, the Model 6 (All Caucasian/White Preservice Teachers) was such a poor fit the Model would not run. Additionally, Model 4 (All

Minority/Not Asian Female Preservice Teachers) and Model 10 (All Minority/Not Asian Female Preservice Teachers) both passed, suggesting that there was a difference in ethnicity. However, this study does not provide evidence demonstrating ethnic Caucasian/White have positive mathematical beliefs. Given these results, I cannot reject the null hypothesis.

Chapter Summary

This chapter presented the study analysis. First, the CFA analysis for the Models were presented showing Model 1.1, Model 1.2, Model 3, Model 4, and Model 10 all found to be acceptable fits. After the presentation of the results the study hypotheses were analyzed. In the analysis, I rejected the null hypothesis for $H1_1$. I could not reject the null hypothesis for $H1_2$, $H1_3$, $H1_4$.

Chapter 5

Discussion

Summary of the Study

The study answers the following research questions:

Research Questions

In this cross-sectional study, I answered the following questions:

1. Is the hypothesized second-order factor model of mathematical task values and attribution of expectancy tenable for pre-service teachers?
2. To what extent did pre-service teachers' motivational beliefs about mathematics, measured by Mathematical Attribution of Expectancy and Mathematical Task Values, affect the grade level they chose to teach in?
3. Was the hypothesized factor structure valid for different groups of preservice teachers (e.g. caucasian/white, minority/not-asian, male, female)?

Research Question 1

The results suggested the measurement model fits for the overall models (Models 1.1 and 1.2) tested in this study. My results for the factor structure of identity aligned with my expectations of a model fit. Analyzing the models for total population (Model 1.1 and Model 1.2) I found in the results all bivariate correlations among the latent variables were significant and in the direction expected, except the latent variables Utility and Cost. In these models, Utility and Cost demonstrate negative correlations. However, these models still were found to be acceptable fits. Separate trials were done constraining Utility and Cost resulting in models. That change did not result in models with acceptable fit.

These results suggested that both Utility and Cost are necessary to the measurement model, but the fit is not ideal.

Research Question 2

The models for the samples of preservice teachers (Model 1.1, Model 1.2), All Female Preservice Teachers (Model 3), All Minority/Not Asian Female Preservice Teachers(Model 4), and All Minority/Not Asian Preservice Teachers (Model 10), were all tested and found an acceptable fit for an SEM analysis. The models of different levels including All Primary Preservice Teachers (Model 2), Female All Primary Preservice Teachers (Model 5), All All Secondary Female Preservice Teachers (Model 7), All Secondary/Middle School Preservice Teachers (Model 8), All Early Primary Preservice Teachers (Model 9), all failed.

In reference to different grade levels, my results presented no evidence of differences in mathematical beliefs across different grade levels. Specifically, the only models I found to be acceptable fit were mixed grade levels. For this purpose, I was unable to conclude preservice teachers in different grades levels have significantly different mathematical beliefs.

Research Question 3

In my study there was evidence of a valid factor structure for different groups of preservice teachers. I analyzed the subpopulations of pre-service teacher by gender and ethnicity. The models including All Minority/Not Asian Female populations (Models 4 and 10) both passed. This demonstrated a valid factor structure for minority groups. Model 6, the model for Caucasian/White

Preservice Teachers, did not converge. This was evidence that the factor structure for Caucasian/White was not valid.

Regarding gender, I found the overall female model (Model 3) to be an acceptable fit, as were both models of overall preservice teacher population, which are predominantly female. As such, I find for females a valid factor structure. However, I was not able to do an analysis of any strictly male populations. As a result, I could not reach a conclusion about factor structure for males or differences across gender.

Discussion of Results

My research successfully utilized SEM as a method to explore mathematical beliefs of preservice teachers. SEM is a technique for estimating, representing, and testing a theoretical model of linear relations among observed and latent variables (Suhr, 2019). My research indicates the technique of SEM was successful in constructing and testing my theoretical preservice teacher model. My study provides further evidence for the successful use of this approach to investigate teacher motivation. Previous educational research has investigated teacher motivation using Structural Equation Modeling (Arifin, 2015; Skaalvik & Skaalvik, 2016; Skaalvik & Skaalvik, 2018). This includes specific research from Canrinus et al. (2012) that included self-efficacy and indicators of identity. Recent research concerning teacher motivation is primarily focused on factors related to teacher attrition, including Skaalvik and Skaalvik's work in identifying factors related to teacher exhaustion and burnout (2011; 2016; 2018; 2019; 2020).

Regarding differences in teachers of different grade levels, limited studies have investigated differences in mathematical attitudes among lower grade-level teachers (Kuklinski & Weinstein 2000) and different levels of math self-efficacy among different grade levels (Eren & Tezel, 2010). My study is the first to measure indicators associated with grade-level choice and apply motivational theories to explain the differences in choice.

The theoretical implications of this research demonstrate the use of the Expectancy Value Theory in the motivation of preservice teachers. No prior research has applied the Expectancy-Value Theory to educational settings for teacher motivational beliefs in mathematics. My research demonstrates that Expectancy Value Theory is an acceptable tool to explain motivational differences for specific pre-service teachers in the domain of mathematics such as female and minority preservice teachers. My research results indicate EVT is not an acceptable tool to explain motivation differences of Caucasian/White preservice teachers. Additionally, my research demonstrates the existence of the four latent variables predicted to exist for mathematical motivation in preservice teachers.

This study is the first to investigate grade-level choices of preservice teachers. Contrary to my expectations, I found the subpopulations of different grade level preservice teachers in this study did not demonstrate different levels of mathematical beliefs. No individual model of preservice teacher of a specific grade-level was found to be an acceptable model fit. Therefore, I found these results suggested that math beliefs of overall preservice teachers do not predict specific grade level choice. My research is not consistent with previous research such as Eren and Tezel (2010), which found greater mathematical efficacy in primary teachers than higher-grade level teachers. Additionally, the limitations of the results regarding ethnicity failed to explain the differences in ethnicity in grade level choice (Bureau of Labor Statistics, 2018).

Math Beliefs and Ethnicity

Regarding ethnicity, I found evidence of positive mathematical beliefs among minority preservice teachers as Model 4 (Minority/Not Asian Female Preservice Teachers), and Model 10 (All Minority/Not Asian Preservice Teachers) were both found to be acceptable fit. My results aligned with previous research that found that generally minority students have lower positive math beliefs excluding Hispanics (Seo et al., 2019). Model 6 (All Caucasian/White Preservice Teachers) failed to converge in Laavan. Bates et al. (2015) offered a potential explanation for the lack of model fit. They said, “Importantly, failure to converge is not due to defects of the estimation algorithm but is a straightforward consequence of attempting to fit a model that is too complex to be properly supported by the data” (p. 2). Thus, I conclude this study’s results did not explain mathematical beliefs among preservice teachers of different genders. Rather, the evidence showed the relationships between these groups were different.

My research showing a difference in Caucasian/White preservice teachers relative to other ethnic groups is aligned with research from Stevens et al. (2004), which found ethnic differences in Math Self-Concept. This is consistent with results from Andersen and Ward (2014), which found differences in Subjective Task Value among different ethnic groups. Andersen and Ward looked at the differences in Subject Task Value among the top 10% of students with different ethnicities on a math placement exam. They found a difference in Utility Value among the ethnic groups, with Caucasians/White scoring the lowest on Utility Value.

As every other model converged in the study except for one, the Caucasian/White Preservice Teacher model, the explanation is unclear. First, the sample itself may not be representative. In other words, the people within the sample may not represent the actual population of Caucasian/White preservice teachers. Second, the underlying theory may be incorrect, or the theory may not be a fit for this study. If something unobserved took place with this model, since I do not have a way to measure the unobserved, I cannot render an analysis. According to Bates et al. (2015), common practice of addressing non-convergent models is to constrain or respecify the model. However, such a practice is beyond the scope of this individual research. Future research can investigate the reasons for the non-convergence of the Caucasian/White preservice teacher model.

Future research that investigates model differences between Caucasian/White preservice teachers and minority preservice teachers may also investigate the reasons for the distribution of different ethnic groups entering the teaching profession. Additionally, future research can investigate the reasons for different ethnic distributions across grade levels. Previous research indicates factors to consider include financial reasons, personality type, skills, abilities, and culture (Bastick, 2000; Han et al., 2016; Kyriacou & Coulthard, 2000; Olsen, 2008; Ribak-Rosenthal, 1994; Super et al., 2010; Topkaya & Uztosun, 2012; Watt & Richardson, 2007; Yu & Bieger, 2013).

Math Beliefs and Gender

Unfortunately, my results were inconclusive on differences in math beliefs of preservice teachers by gender. As I was unable to run a model of exclusively male preservice teachers, I was unable to run a multi-group confirmatory factor analysis with nested models of gender to compare. Previous research indicates there are differences of math beliefs between genders. Gender differences in math beliefs exist at all ages and become more pronounced as students get older (Cvencek et al, 2021; Cvencek, Meltzoff, & Kapur, 2014; Else-Quest, Hyde, & Linn, 2010). Furthermore, males generally have more positive math beliefs than females on a variety of measures (Hyde et al., 1990; Marsh et al., 2005). Additionally, these results are echoed by Gaspard (2015) who found considerable mathematical task values differences in males.

My research finds no evidence of different mathematical beliefs of preservice teachers of different gender. Specifically, as I determined the model for female minority female (Model 4) was an adequate fit, the models for the subpopulation of all female preservice teachers (Model 3) and all female primary (Model 5) both failed. Although previous research (Cushman, 2005; Eren & Tezel, 2010; Johnson & Birkeland, 2003; Leech et al., 2019) indicated that gender may be a factor in explaining grade-level choice as females disproportionally represent lowers grades, my research provides no evidence that mathematical beliefs influence grade level choice for different genders.

Limitations

The major limitation of the study is the size of the samples for analysis. Due to the constraints of sample size and the necessity of a large sample size to run an SEM, many groups were not analyzed in this research. Specifically, the role of mathematical attitudes in males and specific individual minority groups were overlooked. Research by Gottlieb (2018) suggested that Hispanic and African American males had lower predictive STEM attitudes than all other groups. Since this study could not examine male attitudes and the sample sizes were too small to study individual minority groups, further research can sample larger groups to compare each group to better inform the results of this research.

Additionally, a complete analysis of grade level choice was not possible due to an inadequate sample size for populations of preservice teachers entering grades of upper primary, and middle-school preservice samples. Further limitation due to sample size includes a complete investigation of grade level choice for preservice teachers of different gender and ethnicity. I was unable to determine the influence of math beliefs on these variables regarding grade level choice.

Implications for Practice

The findings presented here yield practical implications that will benefit school and district administrators and hiring managers. The results of this study suggest that math beliefs may not be related to grade level choice. As a result, differences in math beliefs may not be as important as previously thought when administrators and hiring managers are considering teacher placement. Additionally, my results challenge assumptions often made by administrators that teachers in different grade levels have different math beliefs. To the extent that such biases influence staffing decisions at different grade levels, my results suggest those biases may not be accurate.

This research also identifies no difference in math beliefs of preservice teacher ethnic groups. Administrators and hiring managers may not need to consider differences in mathematical beliefs when considering candidates for employment. Previous research has demonstrated that minorities need similar role models in STEM (Andersen & Ward, 2014; Gottlieb, 2018). As such, this research demonstrates that hiring these groups likely does not imply a difference in mathematical attitude. Therefore, this research provides evidence that prioritizing the hiring of teachers of ethnicities similar to student populations is unlikely to result in the hiring of teachers with more negative attitudes towards math.

My research also has implications for teacher preparation programs. Currently researchers are interested in the relationship between teacher preparation and math beliefs (Holm & Kajander, 2020; Jamil & Stegelin 2018;

Looney & Steck 2017). Teacher preparation programs have different requirements for different grade levels (Texas Education Agency, 2020; University of Houston, 2019). My study results provide no explicit evidence of differences in preservice teacher math beliefs across grade level beliefs. Administrators of teacher training programs can use this information to implement a program evaluation regarding preservice curriculum related to developing mathematical beliefs. Specifically, these administrators should reconsider the importance of developing mathematical beliefs and focus on developing mathematical ability.

The results have implications for efforts to create opportunities and access for all students to math content and preparation. Teacher quality is a primary factor influencing the effectiveness of student learning (Bhai & Horoi, 2019; Cardichon et al., 2020; Schumacher et al., 2015; Stronge & Hindman, 2003). Previous research indicates that mathematical attitudes are an indicator of the quality of math teacher (Perera & John, 2020; Xu & Qi, 2019) and math achievement of students (Arens et al., 2017; Susperreguy et al., 2018; Timmerman et al., 2017). This research may suggest differences in teacher quality may not be related to mathematical attitudes. This study indicates a need for researchers to investigate further qualities of an effective mathematics teacher.

Additionally, ethnic and gender gaps in math achievement begin in elementary school (Desilver, 2017). This research suggests the source of the math achievement gap may not be differences in teacher math beliefs. Other factors are more important, such as mathematical content knowledge. When teaching future math teachers, the emphasis needs to be on content mastery.

Recommendations for Further Research

The specific use of the EVT to understand domain influence on motivation can apply to future research. This research provides a framework for using the Expectancy Value Theory in education to understand teacher motivations. In addition to mathematics, other domains can be investigated as well. Specifically, rather than mathematics alone, similar models can be tested for different academic topics including language arts and science. The approach used in this study can investigate beliefs of anyone working in the field of education.

Additionally, as complete populations for different grade levels were not investigated, further research can investigate the full role of those motivations in considering grade-level choice. A larger sample including adequate sample sizes of preservice teachers entering lower primary, upper primary, middle, and high school will assist in future research. Additionally, such research can investigate the role of ethnicity and gender with these grade levels.

Further research can investigate differences in mathematical belief in different ethnic groups of preservice teachers. In my study the Caucasian/White model needs further exploration and possible constraining and respecifying the model to investigate the problem with convergence that was found. Additionally, larger sample sizes of other ethnicities may help further explain my research.

Previous research indicates differences in ethnic groups. Stevens et al. (2004) found greater math self-concept in Latino students than other ethnic groups. I introduced bias into my research when I measured all minority groups together in this study. Further research is necessary to explain the differences between these groups.

Moreover, this research does not address the role of mathematical beliefs and gender. I was unable to determine the role of gender in mathematical beliefs due to the limitations of the sample sizes of the individual populations. Further research can investigate these factors with larger sample sizes. Investigating whether overall male populations are motivated by mathematics may explain the role of gender to enter the profession and may help explore the gender imbalance present in the teaching profession.

My research also puts forth the question the importance of mathematical attitudes in teaching. As my results find no differences of mathematical beliefs among teachers of different grade levels, further research can investigate other factors that may be more influential. Research from Hajovsky et al., demonstrates that efficacy itself does not lead to better teaching, rather, teachers with higher efficacy are less likely to harm relationships with students (2020). Further research can investigate the role math beliefs as a mediating factor of more important factors.

Furthermore, this research utilized multiple instruments to develop the survey leaving 38 items to indicate the first level latent variables. Research indicates that an increase of items per factor can affect goodness-of-fit indexes and negatively influence statistical power (Wang, 2015; Xia & Yang, 2019). Additionally, specific research demonstrates that complicated models can introduce Heywood cases (Chen et al., 2001) and complicated models may influence the chi-squared analysis. As this research has Heywood cases and significant chi-squared, the models may be too complicated. Further research can utilize the same models with lesser items, such as four times per factor. Research utilizing 24 items rather than 38 may provide better fitting models that correct the problems with the models found in this research, including the Heywood cases and the significant chi-squared analysis.

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Appendix A: Figures

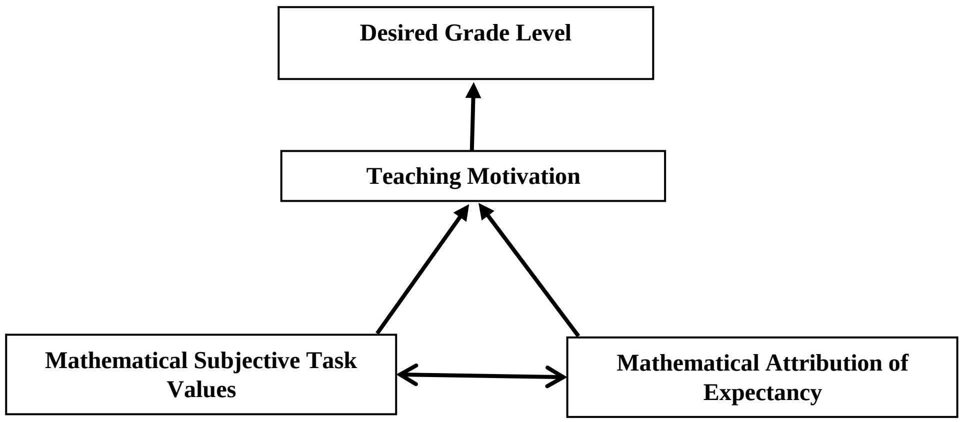

Figure A1: Theoretical Model relating Mathematical Expectancies, Mathematical Subjective Task Values, Teaching Motivation with Desired Grade Level

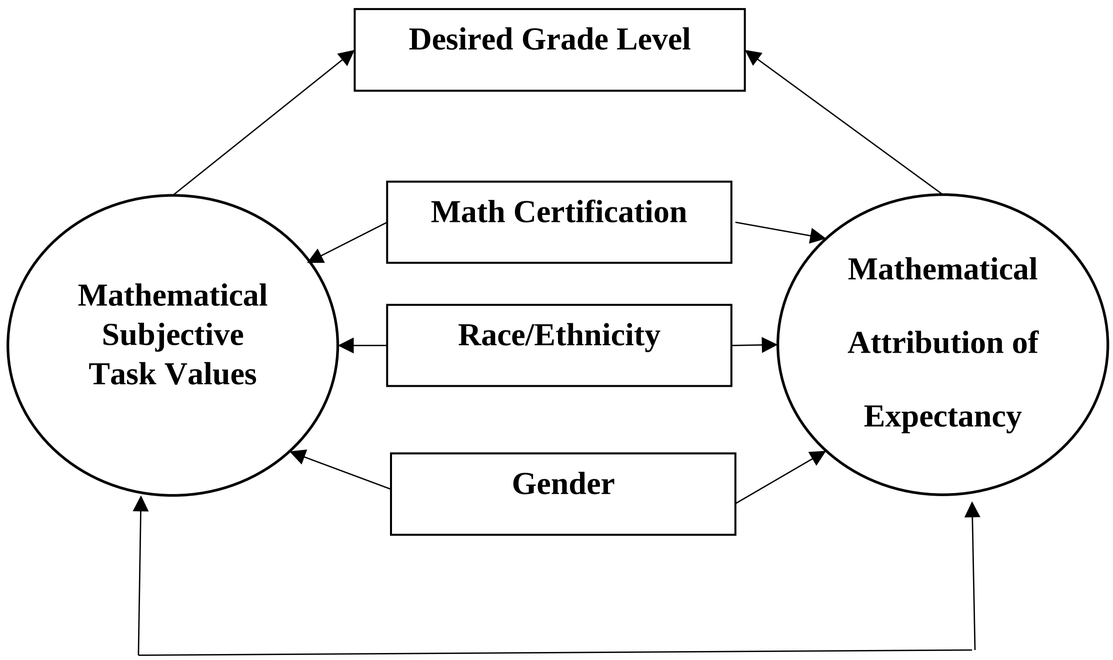

Figure A2: Full SEM Model

Figure 3: Confirmatory Factor Analysis for hypothesized Model

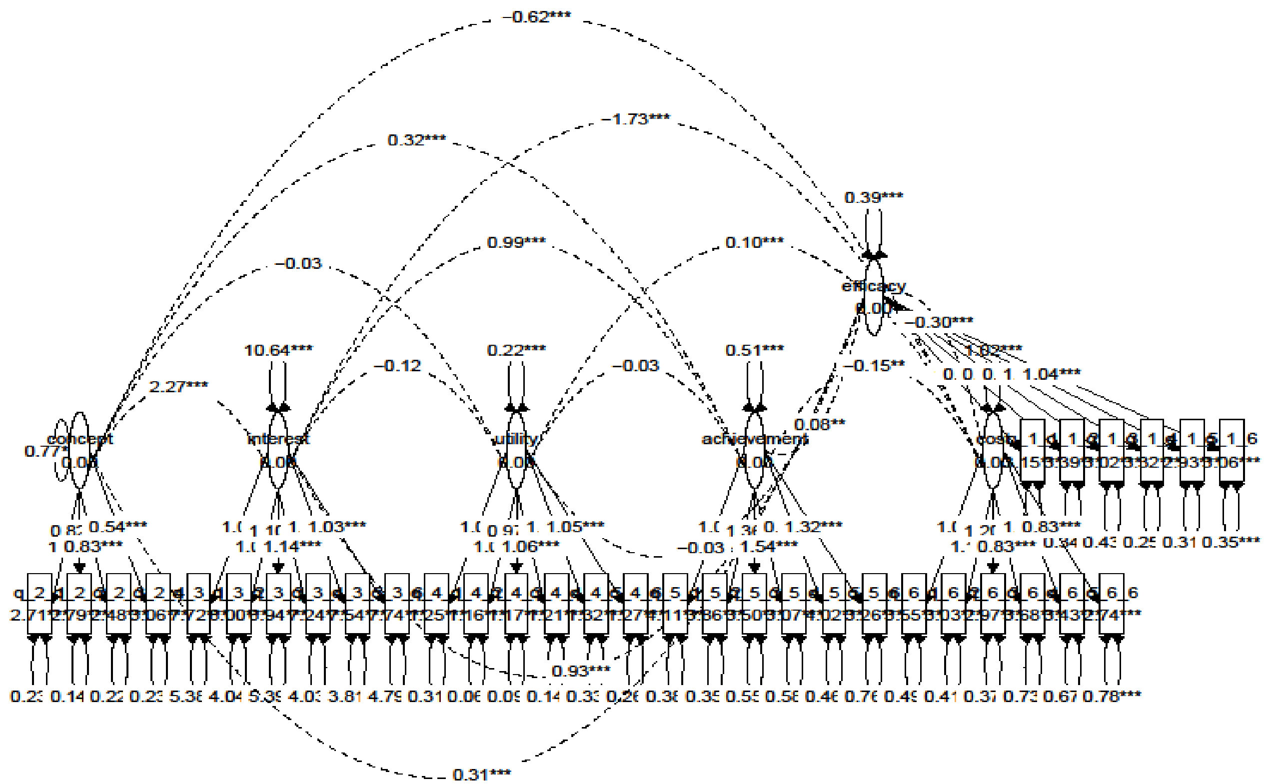

Figure 5
Measurement Model for Model 1.1 (Van Lissa, 2019)

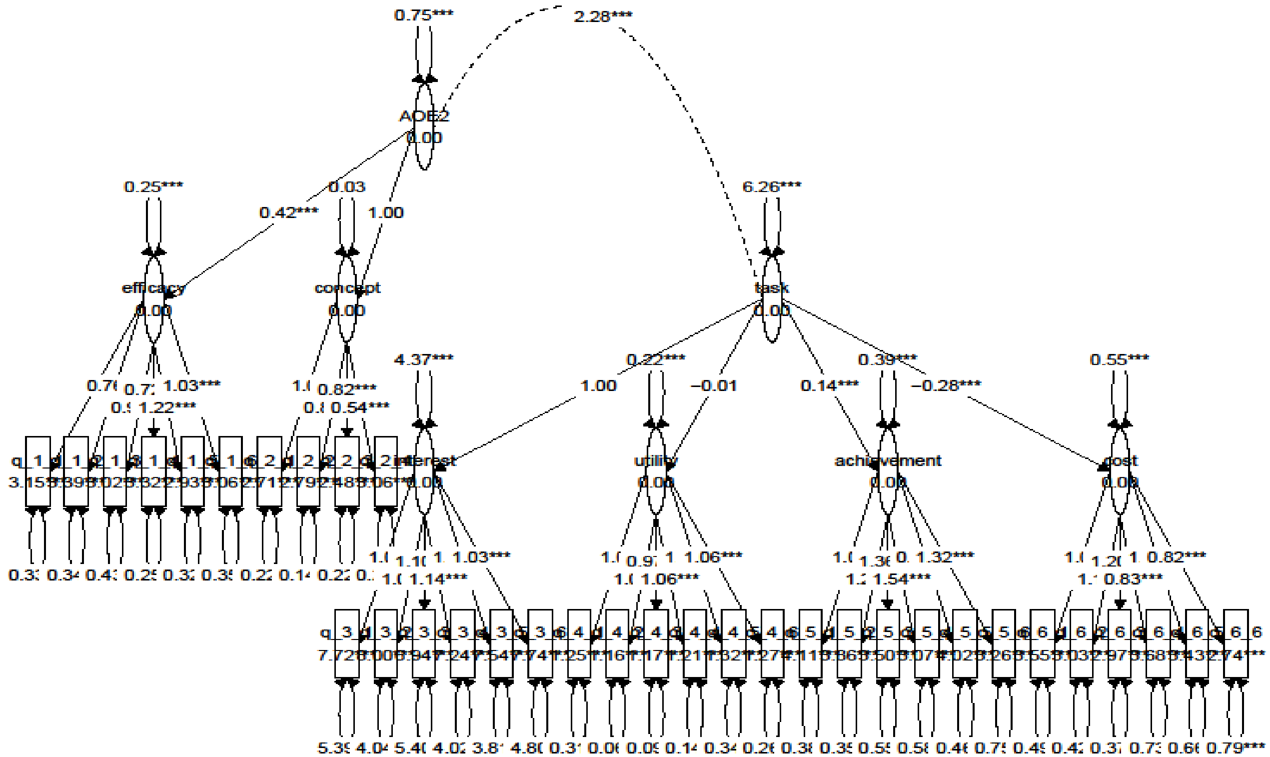

Figure 6
Measurement Model for Model 1.2

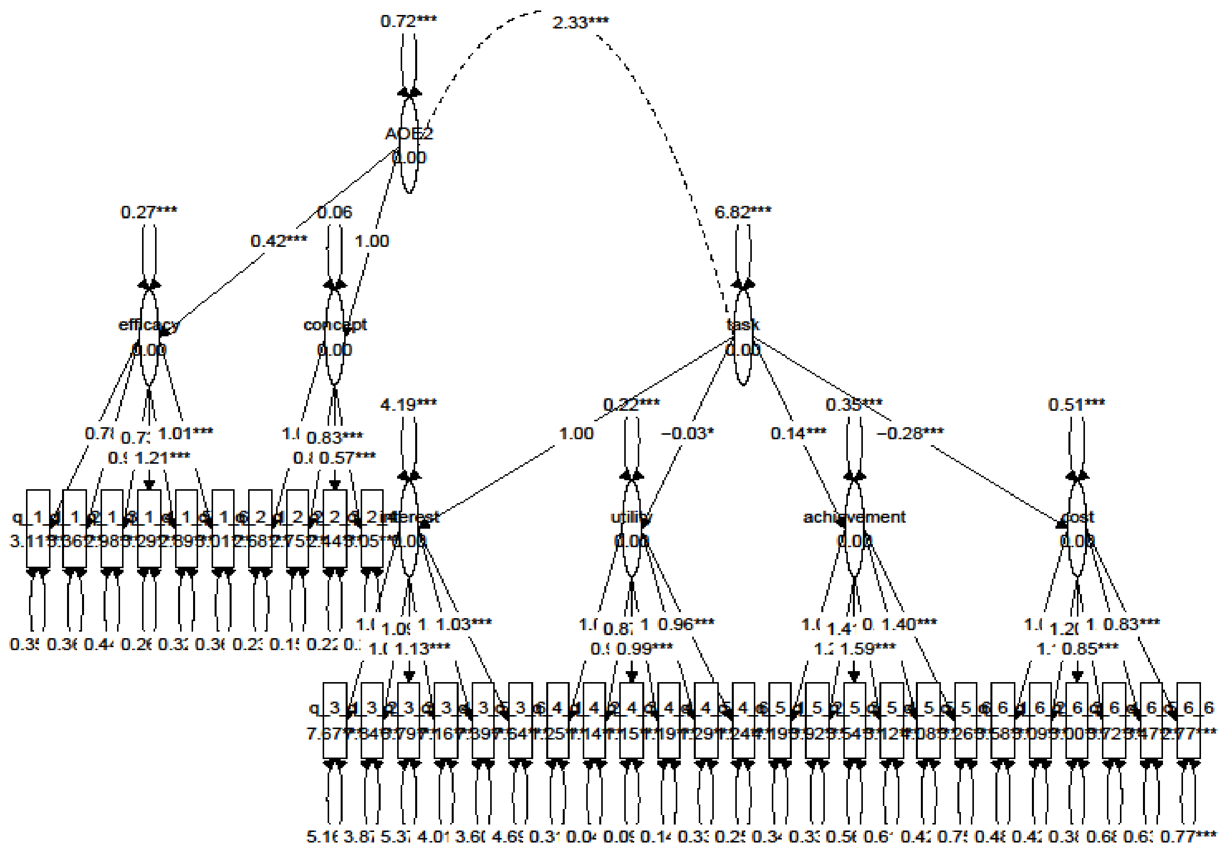

Figure 7
Measurement Model for Model 3

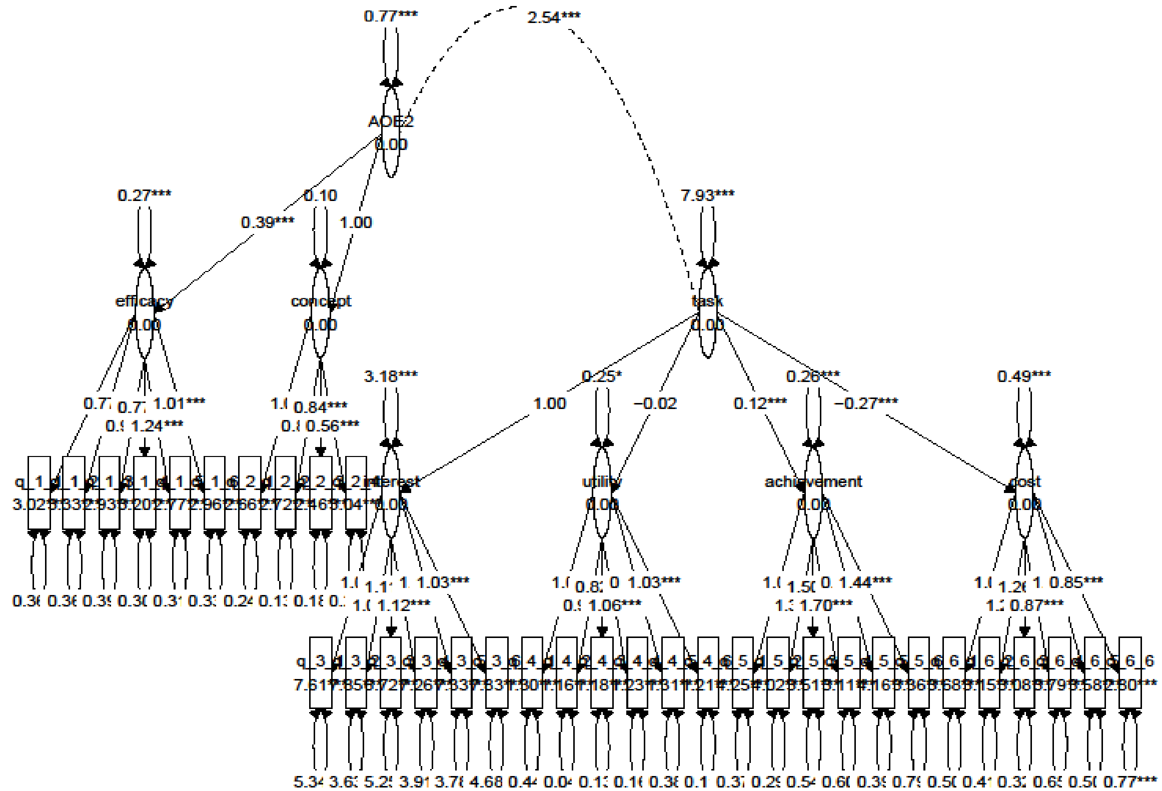

Figure 8

Measurement Model for Model 4

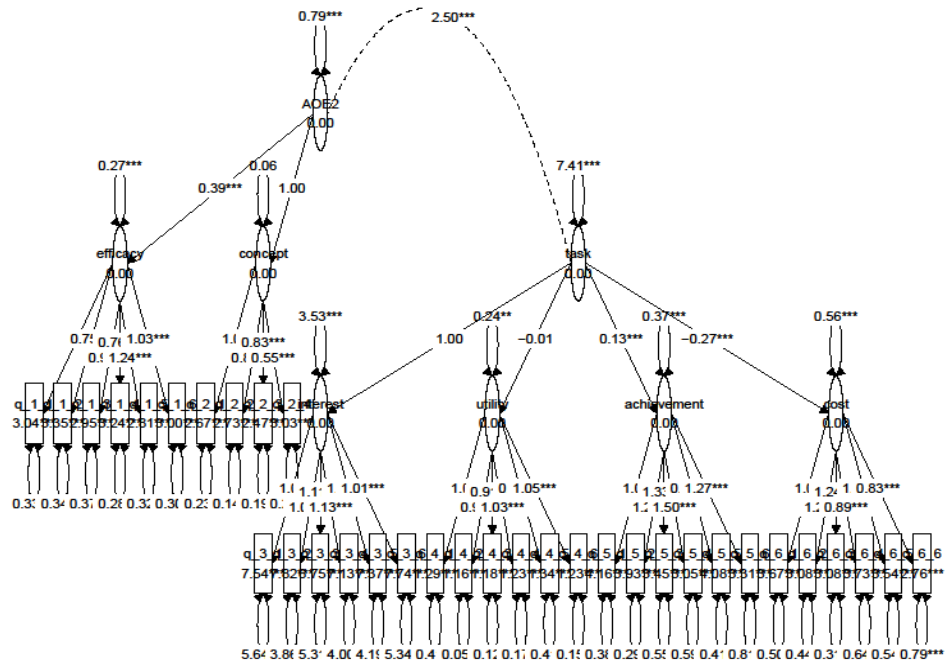

Figure 9

Measurement Model For Model 10

Appendix B: Consent to Participate in Research Form

Consent to Take Part in a Human Research Study

Title of research study:

"AN INVESTIGATION OF THE ROLE OF MATHEMATICAL ATTITUDES IN THE MOTIVATION OF TEACHER GRADE-LEVEL CHOICE USING THE EXPECTANCY-VALUE THEORY."

Investigator: Damian M Berry. This is a research project conducted under the supervision of Dr. Virginia Rangel to fulfill the requirements of an Ed.D. thesis at the University of Houston.

Key Information:

The following focused information is being presented to assist you in understanding the key elements of this study, as well as the basic reasons why you may or may not wish to consider taking part. This section is only a summary; more detailed information, including how to contact the research team for additional information or questions, follows within the remainder of this document under the "Detailed Information" heading.

What should I know about a research study?

- Someone will explain this research study to you.
- Taking part in the research is voluntary; whether or not you take part is up to you.
- You can choose not to take part in.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- You can ask all the questions you want before you decide and can ask questions at any time during the study.

We invite you to take part in a research study about the influence of mathematics in preservice teacher's beliefs about mathematics and their decisions what to teach because you meet the following criteria of being a preservice teacher enrolled in a university

In general, your participation in the research involves complete an online survey, which will take approximately 10 minutes to complete. The survey will ask about your age, ethnicity, and preference of grade choice level to teach; then the survey will ask you questions regarding your personal beliefs about your mathematical ability and questions related to your opinions about *math teaching to measure your Mathematical Self-Efficacy and Mathematical Subjective Task Values.*

The primary risk to you in taking part is there are no known risks, and there is no personal benefit. However, the benefit to society includes information from the study will be presented in educational settings and may be published in a professional journal in the field of mathematics education. Any relationships found in the data analysis may benefit policy and research associated with teacher placement and training. You will not receive compensation for participation; however, should you choose to provide your email address, you will be entered a drawing to win a $100 gift card. After the data collection is complete, a raffle will take place to determine the winner. Arrangements for delivery will be made via email. All participants that provide an email address will receive an email with the results of the study.

Detailed Information:

The following is more detailed information about this study, in addition to the information listed above.

Why is this research being done?

The study is investigating pre-service teachers' beliefs about math and their decisions regarding what to teach. The researcher hopes to gain valuable information about preservice teachers to inform principals and researchers.

How long will the research last?

We expect that you will be in this research study for 10 minutes to complete the survey.

How many people will be studied?

We expect to enroll about 250 people in this research study.

What happens if I say yes, I want to be in this research?

You will answer questions on a survey. The survey will ask about your age, ethnicity, and preference of grade choice level to teach. The survey will additionally collect information regarding your personal beliefs about your mathematical ability and questions related to your opinions about math teaching.

What happens if I do not want to be in this research?

You can choose not to take part in the research, and it will not be held against you. Choosing not to take part will involve no penalty or loss of benefit to which you are otherwise entitled.

What happens if I say yes, but I change my mind later?

You can leave the research at any time, and it will not be held against you.

If you stop being in the research, already collected data that still include your name or other personal information will be removed from the study record.

Is there any way being in this study could be bad for me?

We do not expect any risks related to the research activities. If you choose to take part and undergo a negative event you feel is related to the study, please contact Damian M Berry (DMBerry@uh.edu) or the study team.

Will I receive anything for being in this study?

Once you complete the study, you will be provided an opportunity to give your email address. Should you choose to provide your email address, you will be entered a drawing to win a $100 gift card. After the data collection is complete, a raffle will take place to determine the winner. Arrangements for delivery will be made via email. All participants that provide an email address will receive an email with the results of the study.

Will being in this study help me in any way?

We cannot promise any benefits to you or others from your taking part in this research. However, possible benefits include participating in a study that will help researchers, policymakers, and school administrators improve public education.

What happens to the information collected for the research?

Your taking part in this project is anonymous, and the information you provide cannot be linked to your identity.

We may share and publish the results of this research. However, unless otherwise detailed in this document, we will keep your name and other identifying information confidential.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, you should talk to the research team at Vrangel4@centural.uh.edu or 713-743-0343.

This research has been reviewed and approved by the University of Houston Institutional Review Board (IRB). You may also talk to them at (713) 743-9204 or cphs@central.uh.edu if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.
- You have questions about your rights as a research subject.
- You want to get information or provide input about this research

"I have read the consent information and agree to take part in the research."

☐ Yes

☐ No

Are you at least 18 years old?

- ☐ Yes
- ☐ No

Appendix C: Survey Instrument

Survey Questions

1. Are you at least 18 years old?

   - ☐ Yes
   - ☐ No

2. Are you in an education program pursuing a bachelor’s degree?

   - ☐ Yes
   - ☐ No

3. Are you currently seeking a Master of Arts in Teaching (MAT)?

   - ☐ Yes
   - ☐ No

4. Are you currently enrolled in an alternative certification program?

   - ☐ Yes
   - ☐ No

5. Which best considers your teaching level

- ☐ Specialist
- ☐ Non-Specialist

6. Are you planning on pursuing a certification in mathematics?

- ☐ Yes
- ☐ No

7. Which level do you anticipate to teach??

- K-2 Grade (Lower Primary)
- 3-5 Grade (Upper Primary)
- 6-8 Grade (Middle School)
- 9-12 Grade (Secondary School)

8. Which race/ethnicity best describes you?

- ☐ White/ /Non-Hispanic
- ☐ American Indian/Alaska Native
- ☐ Asian
- ☐ Black or African American
- ☐ Native Hawaiian/Pacific Islander
- ☐ Hispanic or Latino

- ☐ Other

9. Which best describes your gender?

- ☐ Male
- ☐ Female
- ☐ Other

The following questions relate to your individual mathematical beliefs

10. How confident do you feel about calculating how many square feet of tile you need to cover a floor?

- Very Confident
- Confident
- Not Confident
- Not Very Confident

10. How confident do you feel about calculating how much cheaper a TV would be after a 30% discount?

- Very Confident
- Confident
- Not Confident

- Not Very Confident

11. How confident do you feel about using a train timetable to work out how long it would take to get from one place to another?

- Very Confident
- Confident
- Not Confident
- Not Very Confident

12. How confident do you feel about understanding graphs presented in newspapers?

- Very Confident
- Confident
- Not Confident
- Not Very Confident

13. How confident do you feel about finding the actual distance between two places on a map with a 1:100 scale?

- Very Confident
- Confident
- Not Confident
- Not Very Confident

14. How confident do you feel about calculating the gas mileage of a car?

- Very Confident
- Confident
- Not Confident
- Not Very Confident

The following questions relate to your personal beliefs about your confidence in mathematics.

15. I have always believed that mathematics is one of my best subjects.

- Strongly agree
- Agree
- Disagree
- Strongly Disagree

16. I learn mathematics quickly.

- Strongly agree
- Agree
- Disagree
- Strongly Disagree

17. In my mathematics class, I understand even the most difficult work.

- Strongly agree
- Agree
- Disagree
- Strongly Disagree

18. I get good grades in mathematics.

- Strongly agree
- Agree
- Disagree
- Strongly Disagree

(Lee, 2009)

The following questions relate to your interest in mathematics.

19. I find many topics in mathematics to be interesting

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

20. Solving math problems is interesting for me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

21. Mathematics fascinates me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

22. I am interested in doing math problems.

- Strongly Agree
- Agree
- Neutral
- Disagree

- Strongly Disagree

23. It is fun to do math.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

24. Learning new topics in mathematics is interesting.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

25. I find math intellectually stimulating.

- Strongly Agree
- Agree
- Neutral

- Disagree
- Strongly Disagree

The following questions relate to your belief in the usefulness of mathematics

26. There are almost no benefits from knowing mathematics.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

27. I see no point in being able to do math.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

28. Having a solid background in mathematics is worthless.

- Strongly Agree

- Agree
- Neutral
- Disagree
- Strongly Disagree

29. I have little to gain by learning how to do math.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

30. After I graduate, an understanding of math will be useless to me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

31. I do not need math in my everyday life.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

32. Understanding math has many benefits for me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

The following questions relate to your need to excel in mathematics

33. Earning high grades in math is important to me.

- Strongly Agree
- Agree
- Neutral
- Disagree

- Strongly Disagree

34. It is important to me to get top grades in my math classes.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

35. If I do not receive an “A” on a math exam, I am disappointed.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

36. Only a course grade of “A” in math is acceptable to me.

- Strongly Agree
- Agree
- Neutral

- Disagree
- Strongly Disagree

37. I must do well in my math classes.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

38. I would be upset to be just an “average student” in math.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

39. Doing well in math courses is important to me.

- Strongly Agree
- Agree

- Neutral
- Disagree
- Strongly Disagree

The following questions relate to your willingness to learn mathematics

40. Math exams scare me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

41. Trying to do math causes me a lot of anxiety.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

42. Taking math classes scares me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

43. I worry about getting low grades in my math courses.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

44. I have to study much harder for math than for other courses.

- Strongly Agree
- Agree
- Neutral
- Disagree

- Strongly Disagree

45. Mathematical symbols confuse me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

46. Solving math problems is too difficult for me.

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

47. Approximately how old are you?

____

48. If you want to enter the raffle to get a $100 gift card provide your email. You will receive the results of the study.

____

We thank you for your time spent taking this survey.

Your response has been recorded.

Appendix D: Auxiliary Tables

Table D1

Loading Items and Associated First Order Latent Constructs in the Proposed Mathematical Belief Model

Variable Per Latent Construct	Description	Initial Scale	Reverse Code
Math Self Efficacy			
q_1_1	How confident do you feel about calculating how many square feet of tile you need to cover a floor?	1-4; NVC-VC	NA
q_1_2	How confident do you feel about calculating how much cheaper a TV would be after a 30% discount?	1-4; NVC-VC	NA
q_1_3	How confident do you feel about using a train timetable to work out how long it would take to get from one place to another?	1-4; NVC-VC	NA

q_1_4	How confident do you feel about understanding graphs presented in newspapers?	1-4; NVC-VC	NA
q_1_5	How confident do you feel about finding the actual distance between two places on a map with a 1:100 scale?	1-4; NVC-VC	NA
q_1_6	How confident do you feel about calculating the gas mileage of a car?	1-4; NVC-VC	NA
Math Self-Concept			
q_2_1	I have always believed that mathematics is one of my best subjects.	1-4; SD-SA	NA
q_2_2	I learn mathematics quickly.	1-4; SD-SA	NA
q_2_3	In my mathematics class, I understand even the most difficult work.	1-4; SD-SA	NA
q_2_4	I get good grades in mathematics	1-4; SD-SA	NA
Interest			

q_3_1	I find many topics in mathematics to be interesting	1-4; SD-SA	NA
q_3_2	Solving math problems is interesting for me.	1-4; SD-SA	NA
q_3_3	Mathematics fascinates me.	1-4; SD-SA	NA
q_3_4	I am interested in doing math problems.	1-4; SD-SA	NA
q_3_5	It is fun to do math.	1-4; SD-SA	NA
q_3_6	Learning new topics in mathematics is interesting.	1-4; SD-SA	NA
q_3_7	I find math intellectually stimulating.	1-4; SD-SA	NA
General Utility			
q_4_1	There are almost no benefits from knowing mathematics.	1-5; SWD-SA	NA
q_4_2	I see no point in being able to do math.	1-5; SWD-SA	NA
q_4_3	Having a solid background in mathematics is worthless.	1-5; SWD-SA	NA

q_4_4	I have little to gain by learning how to do math.	1-5; SWD-SA	NA
q_4_5	After I graduate, an understanding of math will be useless to me.	1-5; SWD-SA	NA
q_4_6	I do not need math in my everyday life.	1-5; SWD-SA	NA
q_4_7	Understanding math has many benefits for me.	1-5; SWD-SA	1-5; SA-SWD
Need for High Achievement			
q_5_1	Earning high grades in math is important to me.	1-5; SD-SA	NA
q_5_2	It is important to me to get top grades in my math classes.	1-5; SD-SA	NA
q_5_3	If I do not receive an “A” on a math exam, I am disappointed.	1-5; SD-SA	NA

q_5_4	Only a course grade of "A" in math is acceptable to me.	1-5; SD-SA	NA
q_5_5	I must do well in my math classes.	1-5; SD-SA	NA
q_5_6	I would be upset to be just an "average student" in math.	1-5; SD-SA	NA
q_5_7	Doing well in math courses is important to me.	1-5; SD-SA	NA
Personal Cost			
q_6_1	Math exams scare me.	1-5; SD-SA	NA
q_6_2	Trying to do math causes me a lot of anxiety.	1-5; SD-SA	NA
q_6_3	Taking math classes scares me.	1-5; SD-SA	NA
q_6_4	I worry about getting low grades in my math courses.	1-5; SD-SA	NA
q_6_5	I have to study much harder for math than for other courses.	1-5; SD-SA	NA

q_6_6	Mathematical symbols confuse me.	1-5; SD-SA	NA
q_6_7	Solving math problems is too difficult for me.	1-5; SD-SA	NA

*Initial Scales

- SD-SA Strongly Disagree – Strongly Agree
- SWD-SA Somewhat Disagree – Strongly Agree
- NVC-VC Not Very Confident – Very Confident

Table D2

Descriptive Statistics for Survey Items

	Mean	Standard Error of Mean	Standard Deviation	Skewness	Standard Error of Skewness	Kurtosis	Standard Error of Kurtosis
Math Self Efficacy							
MSE1	3.15	0.05	0.847	-0.832	0.129	0.121	0.258
MSE2	3.39	0.04	0.749	-1.198	0.129	1.166	0.258
MSE3	3.021	0.05	0.882	-0.593	0.129	-0.406	0.258
MSE4	3.32	0.04	0.67	-0.713	0.129	0.359	0.258
MSE5	2.935	0.05	0.946	-0.417	0.129	-0.868	0.258
MSE6	3.058	0.05	0.876	-0.597	0.129	-0.452	0.258
Math Self-Concept							
MSC1	2.71	0.05	1.004	-0.254	0.129	-1.016	0.258
MSC2	2.79	0.04	0.817	-0.193	0.129	-0.543	0.258
MSC3	2.48	0.05	0.865	0.026	0.129	-0.647	0.258
MSC4	3.06	0.04	0.678	-0.569	0.129	0.825	0.258
Interest							
I1	7.72	0.21	4.009	-0.808	0.129	-1.287	0.258
I2	8	0.21	3.91	-0.967	0.129	-0.993	0.258
I3	6.94	0.23	4.28	-0.391	0.129	-1.805	0.258
I4	7.238	0.23	4.231	-0.548	0.129	-1.650	0.258
I5	7.538	0.22	4.11	-0.703	0.129	-1.449	0.258
I6	7.74	0.21	4.016	-0.823	0.129	-1.261	0.258
I7	8.877	0.18	3.389	-1.644	0.129	0.854	0.258
General Utility							
GU1	1.25	0.04	0.73	3.141	0.129	9.509	0.258
GU2	1.159	0.03	0.535	3.899	0.129	16.027	0.258
GU3	1.166	0.03	0.55	3.560	0.129	12.560	0.258

GU4	1.207	0.03	0.622	3.166	0.129	9.580	0.258
GU5	1.319	0.04	0.795	2.599	0.129	6.003	0.258
GU6	1.275	0.04	0.712	2.639	0.129	6.300	0.258
GU7	2.145	0.07	1.338	1.114	0.129	0.002	0.258
Need For High Achievement							
NFHA1	4.107	0.05	0.944	-1.176	0.129	1.214	0.258
NFHA2	3.861	0.06	1.057	-0.854	0.129	0.115	0.258
NFHA3	3.5	0.07	1.219	-0.443	0.129	-0.819	0.258
NFHA4	3.07	0.07	1.335	-0.016	0.129	-1.144	0.258
NFHA5	4.017	0.05	0.968	-1.056	0.129	0.968	0.258
NFHA6	3.265	0.07	1.281	-0.190	0.129	-1.035	0.258
NFHA7	4.082	0.05	0.971	-1.159	0.129	1.181	0.258
Personal Cost							
PC1	3.554	0.07	1.229	-0.568	0.129	-0.684	0.258
PC2	3.03	0.07	1.333	-0.030	0.129	-1.157	0.258
PC3	2.967	0.07	1.355	-0.004	0.129	-1.232	0.258
PC4	3.68	0.06	1.195	-0.768	0.129	-0.301	0.258
PC5	3.435	0.07	1.371	-0.354	0.129	-1.174	0.258
PC6	2.736	0.07	1.215	0.257	0.129	-0.884	0.258
PC7	2.554	0.06	1.18	0.365	0.129	-0.748	0.258

Note: MSE = Math Self Efficacy Indicator, MSC = Math Self-Concept Indicator, I= Interest indicator, GU = General Utility Indicator, NFHA = Need for High Achievement Indicator, PC = Personal Cost Indicator

***. Correlation is significant at the 0.01 level (2-tailed*

Table D3

Correlation Coefficients, Effect Size, Relative Size and Covariance between Items.

<u>Math Self-Efficacy</u>							
MSE1	**Correlation**	-					
	Effect Size						
	Relative Size						
	Covariance						
MSE2	**Correlation**	.561**	-				
	Effect Size	0.31472					
	Relative Size	medium					
	Covariance	0.356					
MSE3	**Correlation**	.438**	.372**	-			
	Effect Size	0.19184	0.13838				
	Relative Size	small	small				
	Covariance	0.327	0.245				
MSE4	**Correlation**	.478**	.434**	.512**	-		
	Effect Size	0.22848	0.18836	0.26214			
	Relative Size	medium	small	medium			
	Covariance	0.271	0.218	0.303			
MSE5	**Correlation**	.580**	.455**	.525**	.555**	-	
	Effect Size	0.3364	0.20703	0.27563	0.30803		
	Relative Size	medium	medium	medium	medium		
	Covariance	0.465	0.323	0.438	0.353		
MSE6	**Correlation**	.507**	.427**	.581**	.465**	.626**	-
	Effect Size	0.25705	0.18233	0.33756	0.21623	0.391876	
	Relative Size	medium	small	medium	medium	medium	

	Covariance	0.376	0.28	0.449	0.273	0.519					
Math Self-Concept											
MSC1	**Correlation**	.466**	.406**	.294**	.239**	.442**	.313**	-			
	Effect Size	0.21716	0.16484	0.08644	0.05712	0.195364	0.097969				
	Relative Size	medium	small	small	small	small	small				
	Covariance	0.397	0.305	0.26	0.161	0.421	0.276				
MSC2	**Correlation**	.432**	.390**	.317**	.291**	.434**	.337**	.787**	-		
	Effect Size	0.18662	0.1521	0.10049	0.08468	0.188356	0.113569	0.61937			
	Relative Size	small	small	small	small	small	small	large			
	Covariance	0.299	0.239	0.229	0.16	0.336	0.242	0.648			
MSC3	**Correlation**	.379**	.335**	.342**	.298**	.388**	.290**	.718**	.762**	-	
	Effect Size	0.14364	0.11223	0.11696	0.0888	0.150544	0.0841	0.51552	0.580644		
	Relative Size	small	small	small	small	small	small	large	large		
	Covariance	0.277	0.217	0.26	0.173	0.318	0.219	0.623	0.539		
MSC4	**Correlation**	.316**	.304**	.223**	.251**	.313**	.189**	.580**	.627**	.643**	-
	Effect Size	0.09986	0.09242	0.04973	0.063	0.097969	0.035721	0.3364	0.393129	0.41345	
	Relative Size	small	small	small	small	small	small	medium	medium	medium	
	Covariance	0.182	0.155	0.134	0.114	0.201	0.112	0.396	0.348	0.377	
Interest											
I1	**Correlation**	.379**	.312**	.224**	.182**	.266**	.221**	.626**	.562**	.570**	.482**
	Effect Size	0.14364	0.09734	0.05018	0.03312	0.070756	0.048841	0.39188	0.315844	0.3249	0.23232
	Relative Size	small	small	small	small	small	small	medium	medium	medium	medium
	Covariance	1.285	0.936	0.79	0.489	1.008	0.778	2.52	1.844	1.971	1.311
I2	**Correlation**	.390**	.367**	.234**	.182**	.345**	.242**	.676**	.521**	.549**	.448**
	Effect Size	0.1521	0.13469	0.05476	0.03312	0.119025	0.058564	0.45698	0.271441	0.3014	0.2007

	Relative Size	small	small	small	small	small	small	medium	medium	medium	medium
	Covariance	1.289	1.074	0.805	0.476	1.277	0.828	2.655	1.666	1.854	1.188
I3	**Correlation**	.395**	.310**	.214**	.173**	.298**	.220**	.630**	.565**	.569**	.440**
	Effect Size	0.15603	0.0961	0.0458	0.02993	0.088804	0.0484	0.3969	0.319225	0.32376	0.1936
	Relative Size	small	small	small	small	small	small	medium	medium	medium	small
	Covariance	1.431	0.993	0.809	0.497	1.207	0.825	2.709	1.981	2.105	1.277
I4	**Correlation**	.389**	.294**	.239**	.165**	.331**	.252**	.690**	.606**	.579**	.438**
	Effect Size	0.15132	0.08644	0.05712	0.02723	0.109561	0.063504	0.4761	0.367236	0.33524	0.19184
	Relative Size	small	small	small	small	small	small	medium	medium	medium	small
	Covariance	1.391	0.932	0.891	0.469	1.326	0.935	2.934	2.098	2.116	1.257
I5	**Correlation**	.414**	.317**	.260**	.171**	.351**	.222**	.651**	.592**	.570**	.447**
	Effect Size	0.1714	0.10049	0.0676	0.02924	0.123201	0.049284	0.4238	0.350464	0.3249	0.19981
	Relative Size	small	small	small	small	small	small	medium	medium	medium	small
	Covariance	1.439	0.977	0.943	0.472	1.363	0.8	2.687	1.992	2.022	1.246
I6	**Correlation**	.371**	.315**	.254**	.162**	.317**	.229**	.597**	.514**	.542**	.452**
	Effect Size	0.13764	0.09923	0.06452	0.02624	0.100489	0.052441	0.35641	0.264196	0.29376	0.2043
	Relative Size	small	small	small	small	small	small	medium	medium	medium	medium
	Covariance	1.262	0.947	0.899	0.436	1.204	0.804	2.408	1.688	1.879	1.231
I7	**Correlation**	.384**	.408**	.236**	.268**	.334**	.218**	.525**	.495**	.459**	.427**
	Effect Size	0.14746	0.16646	0.0557	0.07182	0.111556	0.047524	0.27563	0.245025	0.21068	0.18233
	Relative Size	small	small	small	small	small	small	medium	medium	medium	small
	Covariance	1.1	1.036	0.706	0.61	1.07	0.648	1.789	1.373	1.342	0.982
General Utility											
GU1	**Correlation**	-0.068	-.129*	0.029	-0.009	-0.037	-0.02	0.009	0.05	0.077	0.028
	Effect Size	0.00462	0.01664	0.00084	8.10E-05	0.001369	0.0004	8.10E-05	0.0025	0.00593	0.00078

	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.043	-0.072	0.019	-0.005	-0.026	-0.013	0.007	0.031	0.049	0.014
GU2	**Correlation**	-0.06	-0.118	0.009	-0.038	-0.07	-0.013	-0.052	0.003	0.013	-0.072
	Effect Size	0.0036	0.01392	8.10E-05	0.00144	0.0049	0.000169	0.0027	0.000009	0.00017	0.00518
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.029	-0.051	0.004	-0.014	-0.038	-0.006	-0.03	0.001	0.007	-0.028
GU3	**Correlation**	-0.009	-0.082	0.003	-0.028	-0.017	-0.004	-0.018	0.003	0.021	-0.044
	Effect Size	8.10E-05	0.00672	9.00E-06	0.00078	0.000289	0.000016	0.00032	0.000009	0.00044	0.00194
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.004	-0.034	0.002	-0.01	-0.009	-0.002	-0.01	0.001	0.01	-0.017
GU4	**Correlation**	-0.088	-.120*	-0.024	-0.064	-.112*	-0.05	-0.101	-0.061	-0.033	-.151**
	Effect Size	0.00774	0.0144	0.00058	0.0041	0.012544	0.0025	0.0102	0.003721	0.00109	0.0228
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.047	-0.057	-0.014	-0.027	-0.066	-0.028	-0.064	-0.032	-0.018	-0.064
GU5	**Correlation**	-.162**	-.120*	-0.042	-0.068	-.140**	-0.06	-.133*	-0.101	-0.076	-.163**
	Effect Size	0.02624	0.0144	0.00176	0.00462	0.0196	0.0036	0.01769	0.010201	0.0	0.02657
	Relative Size	small	small	small	small	small	small	small	small	large	small
	Covariance	-0.109	-0.072	-0.03	-0.037	-0.106	-0.042	-0.107	-0.066	-0.052	-0.089
GU6	**Correlation**	-0.062	-.123*	0.001	0.012	-0.029	-0.027	-0.072	0.02	-0.001	-0.028
	Effect Size	0.00384	0.01513	1.00E-06	0.00014	0.000841	0.000729	0.00518	0.0004	1.00E-06	0.00078
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.038	-0.067	0	0.006	-0.02	-0.017	-0.052	0.012	-0.001	-0.014
GU7	**Correlation**	-.108*	-.207**	-0.025	-0.076	-0.044	-0.076	-.139**	-.109*	-0.056	-.141**
	Effect Size	0.01166	0.04285	0.00063	0.00578	0.001936	0.005776	0.01932	0.011881	0.00314	0.01988

	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.122	-0.207	-0.029	-0.068	-0.055	-0.088	-0.187	-0.119	-0.064	-0.128
<u>Need For High Achievement</u>											
NFHA 1	**Correlation**	.128*	.185**	0.071	0.104	0.088	0.047	.255**	.269**	.331**	.409**
	Effect Size	0.01638	0.03423	0.00504	0.01082	0.007744	0.002209	0.06503	0.072361	0.10956	0.16728
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.103	0.132	0.06	0.066	0.079	0.039	0.243	0.209	0.272	0.263
NFHA 2	**Correlation**	.132*	.199**	0.091	0.092	0.092	-0.009	.312**	.284**	.395**	.408**
	Effect Size	0.01742	0.0396	0.00828	0.00846	0.008464	0.000081	0.09734	0.080656	0.15603	0.16646
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.118	0.158	0.085	0.065	0.092	-0.008	0.331	0.246	0.361	0.293
NFHA 3	**Correlation**	.176**	.238**	.145**	0.081	.121*	0.057	.315**	.280**	.357**	.334**
	Effect Size	0.03098	0.05664	0.02103	0.00656	0.014641	0.003249	0.09923	0.0784	0.12745	0.11156
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.181	0.217	0.155	0.066	0.139	0.061	0.386	0.279	0.375	0.276
NFHA 4	**Correlation**	.118*	.185**	0.101	0.03	0.102	0.01	.358**	.336**	.396**	.381**
	Effect Size	0.01392	0.03423	0.0102	0.0009	0.010404	0.0001	0.12816	0.112896	0.15682	0.14516
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.134	0.186	0.119	0.027	0.129	0.012	0.482	0.368	0.457	0.345
NFHA 5	**Correlation**	.149**	.228**	0.088	0.06	.114*	0.049	.303**	.302**	.322**	.355**
	Effect Size	0.0222	0.05198	0.00774	0.0036	0.012996	0.002401	0.09181	0.091204	0.10368	0.12603
	Relative Size	small	small	small	small	small	small	small	small	small	small

	Covariance	0.122	0.165	0.075	0.039	0.104	0.041	0.294	0.239	0.269	0.233
NFHA 6	**Correlation**	.146**	.199**	.119*	0.037	.119*	0.041	.375**	.397**	.434**	.415**
	Effect Size	0.02132	0.0396	0.01416	0.00137	0.014161	0.001681	0.14063	0.157609	0.18836	0.17223
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.158	0.191	0.135	0.032	0.144	0.046	0.484	0.416	0.481	0.361
NFHA 7	**Correlation**	.178**	.274**	0.096	0.094	.178**	0.081	.367**	.316**	.346**	.403**
	Effect Size	0.03168	0.07508	0.00922	0.00884	0.031684	6.64E+21	0.13469	0.099856	0.11972	0.16241
	Relative Size	small	small	small	small	small	large	small	small	small	small
	Covariance	0.146	0.199	0.082	0.061	0.163	0.069	0.358	0.251	0.29	0.265
<u>Personal Cost</u>											
PC1	**Correlation**	-.318**	-.229**	-.200**	-.233**	-.296**	-.208**	-.488**	-.523**	-.417**	-.388**
	Effect Size	0.10112	0.05244	0.04	0.05429	0.087616	0.043264	0.23814	0.273529	0.17389	0.15054
	Relative Size	small	small	small	small	small	small	medium	medium	small	small
	Covariance	-0.331	-0.211	-0.216	-0.192	-0.344	-0.224	-0.602	-0.526	-0.442	-0.323
PC2	**Correlation**	-.355**	-.320**	-.210**	-.278**	-.348**	-.224**	-.532**	-.583**	-.438**	-.446**
	Effect Size	0.12603	0.1024	0.0441	0.07728	0.121104	0.050176	0.28302	0.339889	0.19184	0.19892
	Relative Size	small	small	small	small	small	small	medium	medium	small	small
	Covariance	-0.402	-0.32	-0.248	-0.249	-0.44	-0.262	-0.714	-0.637	-0.505	-0.404
PC3	**Correlation**	-.364**	-.343**	-.268**	-.293**	-.389**	-.275**	-.550**	-.568**	-.451**	-.466**
	Effect Size	0.1325	0.11765	0.07182	0.08585	0.151321	0.075625	0.3025	0.322624	0.2034	0.21716
	Relative Size	small	small	small	small	small	small	medium	medium	medium	medium
	Covariance	-0.419	-0.349	-0.32	-0.267	-0.5	-0.327	-0.751	-0.631	-0.528	-0.429
PC4	**Correlation**	-.243**	-.207**	-.139**	-.206**	-.240**	-.155**	-.356**	-.384**	-.288**	-.329**
	Effect Size	0.05905	0.04285	0.01932	0.04244	0.0576	0.024025	0.12674	0.147456	0.08294	0.10824

	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.247	-0.187	-0.147	-0.166	-0.274	-0.163	-0.43	-0.378	-0.299	-0.269
PC5	**Correlation**	-.320**	-.319**	-.140**	-.226**	-.346**	-.205**	-.552**	-.565**	-.489**	-.488**
	Effect Size	0.1024	0.10176	0.0196	0.05108	0.119716	0.042025	0.3047	0.319225	0.23912	0.23814
	Relative Size	small	small	small	small	small	small	medium	medium	medium	medium
	Covariance	-0.371	-0.327	-0.169	-0.208	-0.449	-0.247	-0.761	-0.634	-0.58	-0.454
PC6	**Correlation**	-.387**	-.354**	-.314**	-.369**	-.422**	-.380**	-.485**	-.502**	-.424**	-.413**
	Effect Size	0.14977	0.12532	0.0986	0.13616	0.178084	0.1444	0.23523	0.252004	0.17978	0.17057
	Relative Size	small	small	small	small	small	small	medium	medium	small	small
PC7	**Correlation**	-.436**	-.446**	-.287**	-.385**	-.411**	-.320**	-.480**	-.527**	-.438**	-.470**
	Effect Size	0.1901	0.19892	0.08237	0.14823	0.168921	0.1024	0.2304	0.277729	0.19184	0.2209
	Relative Size	small	small	small	small	small	small	medium	medium	small	medium
	Covariance	-0.436	-0.395	-0.299	-0.305	-0.459	-0.331	-0.57	-0.51	-0.447	-0.376
Item		**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**GU1**	**GU2**	**GU3**
Interest											
I1	**Correlation**	-									
	Effect Size										
	Relative Size										
	Covariance										
I2	**Correlation**	.713**	-								
	Effect Size	0.50837									
	Relative Size	large									
	Covariance	11.156									
I3	**Correlation**	.715**	.692**								
	Effect Size	0.51123	0.47886								

	Relative Size	large	medium							
	Covariance	12.253	11.561							
I4	**Correlation**	.673**	.755**	.747**	-					
	Effect Size	0.45293	0.57003	0.55801						
	Relative Size	medium	large	large						
	Covariance	11.389	12.462	13.514						
I5	**Correlation**	.682**	.770**	.729**	.800**	-				
	Effect Size	0.46512	0.5929	0.53144	0.64					
	Relative Size	medium	large	large	large					
	Covariance	11.215	12.359	12.814	13.897					
I6	**Correlation**	.730**	.718**	.710**	.726**	.728**	-			
	Effect Size	0.5329	0.51552	0.5041	0.52708	0.529984				
	Relative Size	large	large	large	large	large				
	Covariance	11.732	11.263	12.2	12.316	11.997				
I7	**Correlation**	.614**	.646**	.552**	.582**	.643**	.605**	-		
	Effect Size	0.377	0.41732	0.3047	0.33872	0.413449	0.366025			
	Relative Size	medium	medium	medium	medium	medium	medium			
	Covariance	8.326	8.542	8.004	8.34	8.948	8.224			
General Utility										
GU1	**Correlation**	-0.018	-0.001	-0.027	0.008	0.014	0.005	-0.058	-	
	Effect Size	0.00032	1.00E-06	0.00073	6.40E-05	0.000196	0.000025	0.00336		
	Relative Size	small	small	small	small	small	small	small		
	Covariance	-0.055	-0.001	-0.085	0.024	0.044	0.016	-0.147		
GU2	**Correlation**	-0.075	-0.052	-0.032	-0.017	-0.029	-0.029	-.119*	.633**	-
	Effect Size	0.00563	0.0027	0.00102	0.00029	0.000841	0.000841	0.01416	0.400689	

	Relative Size	small	small	small	small	small	small	small	medium		
	Covariance	-0.172	-0.117	-0.078	-0.042	-0.069	-0.066	-0.23	0.269		
GU3	**Correlation**	-0.082	-0.038	-0.049	0.024	0.003	-0.025	-0.095	.524**	.765**	-
	Effect Size	0.00672	0.00144	0.0024	0.00058	0.000009	0.000625	0.00903	0.274576	0.58523	
	Relative Size	small	small	small	small	small	small	small	medium	large	
	Covariance	-0.183	-0.082	-0.117	0.057	0.008	-0.057	-0.18	0.218	0.244	
GU4	**Correlation**	-.114*	-0.07	-0.065	-0.011	-0.03	-0.061	-0.094	.510**	.691**	.699**
	Effect Size	0.013	0.0049	0.00423	0.00012	0.0009	0.003721	0.00884	0.2601	0.47748	0.4886
	Relative Size	small	small	small	small	small	small	small	medium	medium	medium
	Covariance	-0.288	-0.172	-0.174	-0.029	-0.077	-0.153	-0.201	0.238	0.248	0.245
Interest											
GU5	**Correlation**	-.163**	-.123*	-.107*	-.130*	-0.097	-.140**	-.190**	.425**	.598**	.541**
	Effect Size	0.02657	0.01513	0.01145	0.0169	0.009409	0.0196	0.0361	0.180625	0.3576	0.29268
	Relative Size	small	small	small	small	small	small	small	small	medium	medium
	Covariance	-0.522	-0.383	-0.366	-0.438	-0.317	-0.448	-0.514	0.252	0.273	0.241
GU6	**Correlation**	-0.097	-0.038	-0.013	-0.031	0.013	-0.04	-0.09	.487**	.626**	.571**
	Effect Size	0.00941	0.00144	0.00017	0.00096	0	0	0.0081	0.237169	0.39188	0.32604
	Relative Size	small	small	small	small	small	small	small	medium	medium	medium
	Covariance	-0.283	-0.107	-0.041	-0.094	0.039	-0.118	-0.22	0.263	0.259	0.231
GU7	**Correlation**	-.105*	-0.104	-0.04	-.109*	-0.066	-0.083	-.182**	.118*	.128*	0.061
	Effect Size	0.01103	0.01082	0.0016	0.01188	0.004356	0.006889	0.03312	0.013924	0.01638	0.00372
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-0.563	-0.54	-0.232	-0.618	-0.363	-0.443	-0.825	0.118	0.098	0.046
Need For High Achievement											
NFHA 1	**Correlation**	.275**	.209**	.232**	.197**	.185**	.223**	.206**	-0.083	-.182**	-.181**

	Effect Size	0.07563	0.04368	0.05382	0.03881	0.034225	0.049729	0.04244	0.006889	0.03312	0.03276
	Relative Size	small	small	small	small	small	small	small	small	small	small
NFHA 2	**Covariance**	1.046	0.776	0.944	0.789	0.723	0.85	0.662	-0.059	-0.099	-0.096
	Correlation	.270**	.277**	.291**	.260**	.267**	.249**	.249**	-0.026	-0.077	-0.045
	Effect Size	0.0729	0.07673	0.08468	0.0676	0.071289	0.062001	0.062	0.000676	0.00593	0.00203
	Relative Size	small	small	small	small	small	small	small	small	small	small
NFHA 3	**Covariance**	1.141	1.144	1.315	1.159	1.159	1.057	0.892	-0.021	-0.046	-0.026
	Correlation	.279**	.313**	.306**	.339**	.316**	.303**	.296**	-0.032	-0.05	-0.057
	Effect Size	0.07784	0.09797	0.09364	0.11492	0.099856	0.091809	0.08762	0.001024	0.0025	0.00325
	Relative Size	small	small	small	small	small	small	small	small	small	small
NFHA 4	**Covariance**	1.359	1.49	1.594	1.744	1.579	1.48	1.221	-0.029	-0.035	-0.038
	Correlation	.307**	.287**	.307**	.301**	.338**	.310**	.250**	0.021	0.008	-0.005
	Effect Size	0.09425	0.08237	0.09425	0.0906	0.114244	0.0961	0.0625	0.000441	6.40E-05	2.50E-05
	Relative Size	small	small	small	small	small	small	small	small	small	small
NFHA 5	**Covariance**	1.645	1.499	1.755	1.704	1.858	1.663	1.13	0.021	0.006	-0.004
	Correlation	.236**	.230**	.268**	.257**	.263**	.270**	.255**	-0.056	-0.103	-0.079
	Effect Size	0.0557	0.0529	0.07182	0.06605	0.069169	0.0729	0.06503	0.003136	0.01061	0.00624
	Relative Size	small	small	small	small	small	small	small	small	small	small
NFHA 6	**Covariance**	0.916	0.87	1.112	1.051	1.046	1.05	0.836	-0.04	-0.057	-0.043
	Correlation	.321**	.312**	.341**	.342**	.364**	.354**	.302**	0.069	0.009	0.036
	Effect Size	0.10304	0.09734	0.11628	0.11696	0.132496	0.125316	0.0912	0.004761	8.10E-05	0.0013
	Relative Size	small	small	small	small	small	small	small	small	small	small

	Covariance	1.65	1.564	1.871	1.855	1.92	1.822	1.309	0.066	0.006	0.026
NFHA 7	**Correlation**	.312**	.358**	.326**	.310**	.327**	.364**	.350**	-.149**	-.190**	-.151**
	Effect Size	0.09734	0.12816	0.10628	0.0961	0.106929	0.132496	0.1225	0.022201	0.0361	0.0228
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	1.212	1.358	1.352	1.27	1.302	1.416	1.149	-0.107	-0.105	-0.081
<u>Personal Cost</u>											
PC1	**Correlation**	-.313**	-.296**	-.306**	-.365**	-.354**	-.300**	-.275**	0.041	.117*	0.071
	Effect Size	0.09797	0.08762	0.09364	0.13323	0.125316	0.09	0.07563	0.001681	0.01369	0.00504
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-1.539	-1.417	-1.605	-1.892	-1.786	-1.478	-1.141	0.038	0.082	0.049
PC2	**Correlation**	-.386**	-.402**	-.400**	-.396**	-.428**	-.392**	-.334**	0.07	.163**	0.096
	Effect Size	0.149	0.1616	0.16	0.15682	0.183184	0.153664	0.11156	xxx	0.02657	0.00922
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-2.065	-2.098	-2.288	-2.238	-2.345	-2.102	-1.51	0.07	0.124	0.071
PC3	**Correlation**	-.397**	-.422**	-.411**	-.425**	-.446**	-.418**	-.374**	.116*	.150**	.122*
	Effect Size	0.15761	0.17808	0.16892	0.18063	0.198916	0.174724	0.13988	0.013456	0.0225	0.01488
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-2.159	-2.239	-2.389	-2.437	-2.49	-2.28	-1.72	0.117	0.116	0.092
PC4	**Correlation**	-.218**	-.209**	-.223**	-.233**	-.240**	-.221**	-.169**	-0.024	-0.004	-0.054
	Effect Size	0.04752	0.04368	0.04973	0.05429	0.0576	0.048841	0.02856	0.000576	1.60E-05	0.00292
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-1.05	-0.981	-1.147	-1.182	-1.184	-1.065	-0.69	-0.021	-0.003	-0.036
PC5	**Correlation**	-.372**	-.395**	-.367**	-.379**	-.420**	-.356**	-.293**	0.049	.131*	.124*
	Effect Size	0.13838	0.15603	0.13469	0.14364	0.1764	0.126736	0.08585	2.40E-03	0.01716	0.01538
	Relative Size	small	small	small	small	small	small	small	small	small	small

	Covariance	-2.044	-2.114	-2.151	-2.196	-2.368	-1.958	-1.362	0.05	0.103	0.095
PC6	**Correlation**	-.326**	-.397**	-.346**	-.363**	-.359**	-.375**	-.310**	.112*	.226**	.176**
	Effect Size	0.10628	0.15761	0.11972	0.13177	0.128881	0.140625	0.0961	0.012544	0.05108	0.03098
	Relative Size	small	small	small	small	small	small	small	small	small	small
PC7	**Correlation**	-.395**	-.408**	-.386**	-.390**	-.393**	-.416**	-.417**	.172**	.250**	.225**
	Effect Size	0.15603	0.16646	0.149	0.1521	0.154449	0.173056	0.17389	0.029584	0.0625	0.05063
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	-1.868	-1.88	-1.953	-1.949	-1.904	-1.973	-1.668	0.151	0.169	0.148

Item		**GU4**	**GU5**	**GU6**	**GU7**	**NFHA1**	**NFHA2**	**NFHA3**	**NFHA4**	**NFHA5**	**NFHA6**
Interest											
GU5	**Correlation**	.595**	-								
	Effect Size	0.35403									
	Relative Size	medium									
	Covariance	0.299									
GU6	**Correlation**	.606**	.545**	-							
	Effect Size	0.36724	0.29703								
	Relative Size	medium	medium								
	Covariance	0.276	0.316								
GU7	**Correlation**	0.076	0.104	.135*	-						
	Effect Size	0.00578	0.01082	0.01823							
	Relative Size	small	small	small							
	Covariance	0.064	0.111	0.131							
Need For High Achievement											
NFHA1	**Correlation**	-.265**	-.251**	-.177**	-.255**	-					
	Effect Size	0.07023	0.063	0.03133	0.06503						

	Relative Size	small	small	small	small						
	Covariance	-0.158	-0.19	-0.122	-0.324						
NFHA 2	**Correlation**	-0.1	-0.092	-0.059	-.215**	.777**	-				
	Effect Size	0.01	0.00846	0.00348	0.04623	0.603729					
	Relative Size	small	small	small	small	large					
	Covariance	-0.067	-0.078	-0.045	-0.303	0.779					
NFHA 3	**Correlation**	-0.036	-.112*	0.01	-.105*	.525**	.627**	-			
	Effect Size	0.0013	0.01254	0.0001	0.01103	0.275625	0.393129				
	Relative Size	small	small	small	small	medium	medium				
	Covariance	-0.028	-0.109	0.009	-0.17	0.607	0.807				
NFHA 4	**Correlation**	0.02	-0.098	0.03	-0.087	.510**	.629**	.730**	-		
	Effect Size	0.0004	0.0096	0.0009	0.00757	0.2601	0.395641	0.5329			
	Relative Size	small	small	small	small	medium	medium	large			
	Covariance	0.016	-0.105	0.029	-0.156	0.647	0.888	1.189			
NFHA 5	**Correlation**	-.129*	-.111*	-0.054	-.251**	.627**	.582**	.512**	.587**	-	
	Effect Size	0.01664	0.01232	0.00292	0.063	0.393129	0.338724	0.26214	0.344569		
	Relative Size	small	small	small	small	medium	medium	medium	medium		
	Covariance	-0.078	-0.085	-0.038	-0.325	0.576	0.595	0.603	0.759		
NFHA 6	**Correlation**	0.022	-0.016	0.065	-0.103	.439**	.554**	.637**	.671**	.501**	-
	Effect Size	0.00048	0.00026	0.00423	0.01061	0.192721	0.306916	0.40577	0.450241	0.251	
	Relative Size	small	small	small	small	small	medium	medium	medium	medium	
	Covariance	0.018	-0.016	0.06	-0.176	0.535	0.751	0.994	1.149	0.622	

NFHA 7	**Correlation**	-.208**	-.194**	-.153**	-.309**	.683**	.628**	.553**	.548**	.758**	.544**
	Effect Size	0.04326	0.03764	0.02341	0.09548	0.466489	0.394384	0.30581	0.300304	0.57456	0.29594
	Relative Size	small	small	small	small	medium	medium	medium	medium	large	medium
	Covariance	-0.127	-0.15	-0.108	-0.401	0.629	0.643	0.654	0.71	0.712	0.676
<u>Personal Cost</u>											
PC1	**Correlation**	.148**	.206**	.118*	0.063	-0.068	-0.097	-0.069	-.126*	-0.056	-.194**
	Effect Size	0.0219	0.04244	0.01392	0.00397	0.004624	0.009409	0.00476	0.015876	0.00314	0.03764
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.114	0.202	0.105	0.103	-0.08	-0.126	-0.104	-0.207	-0.067	-0.305
PC2	**Correlation**	.195**	.221**	0.075	0.059	-.128*	-.131*	-0.088	-.113*	-.118*	-.202**
	Effect Size	0.03803	0.04884	0.00563	0.00348	0.016384	0.017161	0.00774	0.012769	0.01392	0.0408
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.164	0.235	0.073	0.105	-0.162	-0.184	-0.142	-0.202	-0.152	-0.346
PC3	**Correlation**	.157**	.207**	0.054	0.05	-.147**	-.119*	-.127*	-.147**	-.153**	-.208**
	Effect Size	0.02465	0.04285	0.00292	0.0025	0.021609	0.014161	0.01613	0.021609	0.02341	0.04326
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.134	0.225	0.053	0.091	-0.19	-0.171	-0.21	-0.266	-0.201	-0.362
PC4	**Correlation**	0.002	.109*	-0.035	0	0.059	-0.015	0.041	-0.039	0.057	-0.079
	Effect Size	4.00E-06	0.01188	0.00123	0	0.003481	0.000225	0.00168	0.001521	0.00325	0.00624
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.002	0.105	-0.03	0	0.067	-0.019	0.059	-0.063	0.066	-0.121
PC5	**Correlation**	.147**	.160**	0.079	0.019	-.165**	-.201**	-.236**	-.291**	-.142**	-.268**
	Effect Size	0.02161	0.0256	0.00624	0.00036	0.027225	0.040401	0.0557	0.084681	0.02016	0.07182
	Relative Size	small	small	small	small	small	small	small	small	small	small

	Covariance	0.126	0.175	0.078	0.036	-0.214	-0.291	-0.395	-0.533	-0.188	-0.472
PC6	**Correlation**	.197**	.215**	.121*	0.081	-.169**	-.178**	-.160**	-.169**	-.175**	-.189**
	Effect Size	0.03881	0.04623	0.01464	0.00656	0.028561	0.031684	0.0256	0.028561	0.03063	0.03572
	Relative Size	small	small	small	small	small	small	small	small	small	small
	N	356	356	356	356	356	356	356	356	356	356
PC7	**Correlation**	.263**	.246**	.159**	0.097	-.213**	-.191**	-.207**	-.174**	-.224**	-.262**
	Effect Size	0.06917	0.06052	0.02528	0.00941	0.045369	0.036481	0.04285	0.030276	0.05018	0.06864
	Relative Size	small	small	small	small	small	small	small	small	small	small
	Covariance	0.195	0.232	0.136	0.153	-0.239	-0.238	-0.298	-0.275	-0.256	-0.397

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Item		**NFHA7**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**
Personal Cost								
PC1	**Correlation**	-0.064	-					
	Effect Size	0.0041						
	Relative Size	small						
	Covariance	-0.076						
PC2	**Correlation**	-.148**	.715**	-				
	Effect Size	0.0219	0.51123					
	Relative Size	small	large					
	Covariance	-0.192	1.172					
PC3	**Correlation**	-.190**	.729**	.797**	-			
	Effect Size	0.0361	0.53144	0.63521				
	Relative Size	small	large	large				
	Covariance	-0.25	1.215	1.445				
PC4	**Correlation**	0.058	.648**	.595**	.624**	-		

	Effect Size	0.00336	0.4199	0.35403	0.38938				
	Relative Size	small	medium	medium	medium				
	Covariance	0.068	0.955	0.955	1.017				
PC5	**Correlation**	-.174**	.669**	.686**	.707**	.590**	-		
	Effect Size	0.03028	0.44756	0.4706	0.49985	0.3481			
	Relative Size	small	medium	medium	medium	medium			
	Covariance	-0.232	1.126	1.256	1.316	0.973			
PC6	**Correlation**	-.206**	.523**	.610**	.605**	.445**	.557**	-	
	Effect Size	0.04244	0.27353	0.3721	0.36603	0.198025	0.310249		
	Relative Size	small	medium	medium	medium	small	medium		
PC7	**Correlation**	-.261**	.525**	.621**	.644**	.443**	.571**	.722**	-
	Effect Size	0.06812	0.27563	0.38564	0.41474	0.196249	0.326041	0.52128	
	Relative Size	small	medium	medium	medium	small	medium	large	
	Covariance	-0.298	0.761	0.979	1.032	0.629	0.925	1.035	

**. Correlation is significant at the 0.05 level (2-tailed).*

Appendix E: IRB Documentation

UNIVERSITY of HOUSTON
DIVISION OF RESEARCH
Institutional Review Boards

APPROVAL OF SUBMISSION

October 31, 2019

Damian Berry

dmberry@uh.edu

Dear Damian Berry:

On October 31, 2019, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	An Investigation of the Role of Mathematical Attitudes in the Motivation of Pre-service Teacher Grade Level Choice using the Expectancy-Value Theorem
Investigator:	Damian Berry
IRB ID:	STUDY00001851
Funding/ Proposed Funding:	Name: Unfunded
Award ID:	
Award Title:	
IND, IDE, or HDE:	None
Documents Reviewed:	• Participate in a Research Study, Category: Recruitment Materials; • Consent.pdf, Category: Consent Form; • Survey Questions, Category: Study tools (ex: surveys, interview/focus group questions, data collection forms, etc.); • D. Berry IRB Final Reviewed.pdf, Category: IRB Protocol; • Recruitment Email, Category: Recruitment Materials;
Review Category:	Exempt
Committee Name:	Not Applicable
IRB Coordinator:	Sandra Arntz

The IRB approved the study on October 31, 2019 ; recruitment and procedures detailed within the approved protocol may now be initiated.

UNIVERSITY of HOUSTON
DIVISION OF RESEARCH
Institutional Review Boards

As this study was approved under an exempt or expedited process, recently revised regulatory requirements do not require the submission of annual continuing review documentation. However, it is critical that the following submissions are made to the IRB to ensure continued compliance:

- Modifications to the protocol prior to initiating any changes (for example, the addition of study personnel, updated recruitment materials, change in study design, requests for additional subjects)
- Reportable New Information/Unanticipated Problems Involving Risks to Subjects or Others
- Study Closure

Unless a waiver has been granted by the IRB, use the stamped consent form approved by the IRB to document consent. The approved version may be downloaded from the documents tab.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system.

Sincerely,

Research Integrity and Oversight (RIO) Office
University of Houston, Division of Research
713 743 9204
cphs@central.uh.edu
http://www.uh.edu/research/compliance/irb-cphs/