1-2015

The Influences of Mathematics Self-Efficacy, Identity, Interest, and Parental Involvement on STEM Achievement in Algebra for Female High School Students

Nicol R. Howard
Chapman University, nicol.howard@gmail.com

The Influences of Mathematics Self-Efficacy, Identity, Interest, and Parental Involvement on STEM Achievement in Algebra for Female High School Students

A Dissertation by

Nicol R. Howard

Chapman University

Orange, California

College of Educational Studies

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Education

January 2015

Committee in charge:

Randy Busse, Ph.D., Chair

Kelly Kennedy, Ph.D.

Michelle Cleary, Ph.D.

The dissertation of Nicol R. Howard is approved.

Randy Busse, Ph.D., Chair

Kelly Kennedy, Ph.D.

Michelle Cleary, Ph.D.

January 2015

The Influences of Mathematics Self-Efficacy, Identity, Interest, and Parental Involvement on STEM Achievement in Algebra for Female High School Students

DEDICATION

This dissertation is lovingly dedicated to my family, especially…

to my husband Keith, for his gentle and genuine support. He stood as my pillar when I couldn't see the walls were leaning, and he generously sacrificed while sharing this vibrant journey with me…and that is how the story goes.

to my children, Micaela and Kamau – may you be motivated and encouraged to reach your dreams…what a story.

to my parents DeEtta, Beverly, Joseph, and James for their words of wisdom and encouragement and their active involvement in my academic pursuits.

ACKNOWLEDGEMENTS

At Chapman University I have had the privilege of working with, and learning from, inspirational professors who have made contributions to my professional and academic experience. My advisor, Dr. Randy Busse, challenged me to think critically about my scholarship and teaching. He has also been a model of someone who effectively balances research, teaching, advising, and family life. Despite his busy schedule, Dr. Busse finds the time to meet to discuss current research, quantitative methodologies, and effective teaching strategies. His dedication to the Educational Psychology field is remarkable and inspiring. Dr. Kelly Kennedy has also presented a positive model throughout my years at Chapman University. Her commitment to faithfully complete all that she takes on does not go unnoticed. Through our numerous discussions, Dr. Kennedy provided support and wisdom related to making decisions about my research and career trajectory. Along with Dr. Busse and Dr. Kennedy, Dr. Cleary influenced the direction and analysis of this dissertation. I appreciate Dr. Cleary's directedness and thoughtful critiques of my past and present research. My committee is a cut above the rest - I am grateful and honored to have had the privilege of working with each of you. One final thank you must go out to Dr. Keith E. Howard for modeling the journey of someone who maintains the learning posture. He inspired me to extend my efforts of pursuing knowledge related to quantitative research methodology, beyond the classroom walls. The knowledge I have gained through those pursuits adds significantly to this dissertation.

ABSTRACT

The Influences of Mathematics Self-Efficacy, Identity, Interest, and Parental Involvement on STEM Achievement in Algebra for Female High School Students

by Nicol R. Howard

The purpose of this study was to determine the predictability of STEM achievement in Algebra for female high school students utilizing mathematics self-efficacy, mathematics interest, mathematics identity, and parental involvement. This study employed data from the High School Longitudinal Study of 2009 (HSLS:09/12) which consisted of 3,938 female eleventh-grade participants randomly selected from 944 public and private high schools during the fall 2009 academic year. The results of a hierarchical multiple regression indicated that mathematics identity was the strongest predictor of STEM achievement for female high school students, regardless of race. In spite of this significant relationship, STEM achievement outcomes are impacted by numerous factors. Further explorations of these factors are needed to provide a more accurate model to predict female high school student achievement in STEM.

TABLE OF CONTENTS

CHAPTER ONE: INTRODUCTION 1
THEORETICAL FRAMEWORK 2
STATEMENT OF THE PROBLEM 3
PURPOSE OF THE STUDY 3
RESEARCH QUESTIONS 4
HYPOTHESES 4
Self-efficacy, Interest, and Identity 5
Parental Involvement 5
SIGNIFICANCE OF THE STUDY 6
OPERATIONAL DEFINITIONS 6

CHAPTER TWO: LITERATURE REVIEW 9
A BRIEF OVERVIEW OF THE STEM CRISIS 11
The Gender Gap in STEM 13
Identity and Gender Stereotypes 15
Persistence in STEM and Parental Support 16
FAMILY FACTORS AND ACHIEVEMENT 17
The Coleman Report 17
Socioeconomic Status 19
Parental Involvement and Achievement 23
SCHOOL FACTORS 27
MOTIVATION 30
Self-Efficacy 31
Identity and Interest 33
DISPARITIES IN STEM 35
CONCLUSION 37

CHAPTER THREE: METHODOLOGY 39
NCES Secondary Longitudinal Study 40
High School Longitudinal Study of 2009/2012 41
HSLS Research and Policy Implications 44
VARIABLES AND SCALES 44
Self-Efficacy 45
Interest 46
Identity 46
Parental Involvement 47
Socio-economic Status Composite 50
Mathematics Theta Score 51
MULTIPLE REGRESSION 53
HIERARCHICAL MULTIPLE REGRESSION 54
Assumptions 56
Strengths and Limitations of HMR 58
Rationale 58

Data Cleaning and Editing 59
Analyses 61
POTENTIAL ETHICAL ISSUES 62

CHAPTER 4: RESULTS 63
Sample Size 63
Multicollinearity 64
Outliers 65
Additional Assumptions 66
Results 71

CHAPTER 5: DISCUSSION 78
Research Hypotheses 78
Implications for Policy and Practice 80
Strengths and Limitations of the Current Study 82
Future Research Directions 85
Future Strategies to Support Identity Development 87
SUMMARY 89

REFERENCES 90

LIST OF TABLES

Table 1. Variables HSLS:09/12 Data File……………………………….……………….105

Table 2. Three Component Matrix for Parental Involvement Scale…..……………....106

Table 3. Two Component Matrix for Parental Involvement Scale….………………...107

Table 4. Demographic Data for Female Sample in the HSLS….…………….……….108

Table 5. Demographic Data for the Study Sample..……………..……………….…….109

Table 6. Matrix of Research Question, Variables, Hypotheses, and Analysis………....110

Table 7. Correlation Matrix for Variables in the Study..….…………………………….111

Table 8. Coefficients for Female High school Students.....………………………….…112

Table 9. Outliers Determined by Casewise Diagnostics…………………………......113

Table 10. HMR Model Summary for Female High school Students.…………………..114

Table 11. ANOVA for HMR Model of Female High school Students………………….115

Table 12. HMR Model Summary for Black/African American Female Students……...116

Table 13. ANOVA for Black/African American Female Students….…….……..……..117

Table 14. Coefficients for Black/African American Female Students………………...118

Table 15. HMR Model Summary for White Female Students……………………..…...119

Table 16. ANOVA for White Female Students…..…….……..………………………...120

Table 17. Coefficients for White Female Students………………...............................121

Table 18. HMR Model Summary for Hispanic Female Students……..........................122

Table 19. ANOVA for Hispanic Female Students…..…….……..……………………...123

Table 20. Coefficients for Hispanic Female Students……………….............................124

Table 21. HMR Model Summary for Asian Female Students……...............................125

Table 22. ANOVA for Asian Female Students……….……..…………………………....126

Table 23. Coefficients for Asian Female Students…………………..................................127

LIST OF FIGURES

Figure 1. A temporal representation of High school Longitudinal Study's Program…......41

Figure 2. Longitudinal design of the HSLS:09/12……………………………………….43

Figure 3. Screeplot used for Catell's (1966) scree test…………………………………..49

Figure 4. Chi-square analysis of population sample and study sample……………….…60

Figure 5. Output of a Normal Q-Q Plot………………………………………………......63

Figure 6. Standardized residual plot of outliers……………………………………......65

Figure 7. Histogram of standardized residuals…………………………………………..66

Figure 8. Partial regression plot: Mathematics Theta Score (MTSC) and SES..………...68

Figure 9. Partial regression plot: MTSC and Mathematics Self-Efficacy……………….68

Figure 10. Partial regression plot: MTSC and Mathematics Identity………..………..69

Figure 11. Partial regression plot: MTSC and Mathematics Interest...…………………69

Figure 12. Partial regression plot: MTSC and Parental Involvement Scale……………..70

Figure 13. Beta and P-values for Predictors, by Race…………………………..………..73

Chapter One: Introduction

American innovators in Science, Technology, Engineering, and Mathematics (STEM) have gained notoriety for the United States as a leader among nations. Unfortunately, our nation is beginning to lose its competitive edge and our students are less prepared. Although STEM initiatives are evolving, the gaps in achievement among various groups persist. Gaps in achievement have been identified in various academic areas, including STEM. Arguably, STEM is an important factor in the growth and development of the United States (Legewie & DiPetre, 2011). According to Emdin (2011), increases in educational achievement also support the growth and well-being of the nation. Despite the need for skilled individuals in STEM fields, populations that may possibly meet the demands are not fully engaged (National Research Council, 2012).

As the diversity of the U.S. population continues to increase, racial minorities represent a larger percentage of the populace in Texas, California, New Mexico, Washington D.C., and Hawaii (Humes, Jones, & Ramirez, 2011). Additionally, the U.S. demand for workers is projected to double resulting in 19 million more jobs than workers to fill positions by 2028. Greater numbers of jobs available may suggest a greater need for students' selections of STEM careers. Furthermore, the growth of minority groups in the educational system would also suggest contributions to the STEM pipeline; however, there is an achievement gap that persists between racial minorities and non-minorities (Guyll, Madon, Prieto, & Scherr, 2010). Such a gap in achievement further contributes to the underrepresentation of certain minorities in STEM courses (NRC, 2012).

According to the National Science Board (2012), women have historically been underrepresented in STEM fields. Blickenstaff (2005) argued that there are multiple

factors contributing to gender disparity – some without merit and others that may contribute significantly to the removal of females from the STEM pipeline. One suggested issue attributed to fewer women in STEM is the nature of science itself. Some researchers have argued that STEM has been a male-dominated field that many females choose to avoid. A male-dominated environment may create some internal conflict for women who pursue a STEM career trajectory.

The nature of science raises questions as to why females may choose not to select STEM courses or careers. Are female students in fact responding to the confrontation of gender-bias? Research indicates that women are faced with more issues than gender-bias in STEM. According to Robnett and Leaper (2013), other factors may include motivation-related self-concepts and social norms. Self-perception in science and math is also a noted challenge for females in STEM (Cole & Espinoza, 2008). Understanding the multiple factors related to achievement provides insight into the existing gap(s) among high school students' achievement in STEM courses; gap(s) which may be associated with home and/or school factors.

Theoretical Framework

Within the domain of academic achievement several motivational theories exist, yet of these theories Bandura (1989) claimed the mechanism of self-efficacy is most influential. This is especially true for individuals who want to stimulate change in their personal being and/or situation on their own. Self-efficacy has been used in educational research to explore interactions that exist between self-efficacy and motivation, academic performance, and achievement. Schunk and Pajares (2002) found that self-efficacy

influenced the types of tasks chosen by individuals, their perseverance with tasks, and the expenditure of effort on any given task.

According to Bandura (1986), perceived self-efficacy can operate as a principal contributor to students' academic progress because individuals assume an active role in their motivation. Motivation has been found to have a mediating effect between self-concept and achievement, as well as self-efficacy and achievement. Deci and Ryan (1995) posited that students with higher motivation have more interest, resulting in better performance, persistence and creativity, higher vitality, higher self-esteem and well-being. The research in this dissertation works within the framework of Bandura's social cognitive theory with the variables of self-efficacy, interest, and identity.

Statement of the Problem

An investigation of academic factors (algebra assessment scores) and non-academic factors (mathematics interest, mathematics identity, mathematics self-efficacy, and parental involvement) may provide insight into the achievement of female high school students, specifically in STEM.

Purpose of the Study

The purpose of this dissertation was to investigate the motivational factors and parental involvement associated with female high school students' STEM achievement in algebra. Specifically, analyses were conducted to determine the statistically significant predictors of achievement for female high school students, as well as differences between females by race.

Research Questions

The objective of the research in this dissertation is to examine how and to what extent STEM experiences in high school relate to academic and non-academic factors that may lead to later success in STEM courses. Because the research questions were framed with long-term implications for female students, by design they will require longitudinal data. To that extent, HSLS:09/12 is the most recently released and available national dataset where researchers collect longitudinal data to address the questions with the variables included in this study. During this research, the following questions were under examination: a) How well do motivation (i.e., self-efficacy, interest, or identity) and parental involvement predict STEM achievement for female high school students? and, b) Do the motivational factors and parental involvement predict achievement for female high school students differently when race is considered?

Hypotheses

Researchers (e.g. Brooks-Gunn, 2003; Howard, 2010) have contended that an observable relationship between socioeconomic status and academic performance exists among high school students. Additionally, prior research results imply that the higher the level of socioeconomic status, self-efficacy, and interest, the higher a student's academic performance (Deci & Ryan, 1995). Thus, it is important to separate the above factors in order to understand the extent to which specific factors predict achievement in STEM for female high school students. The research hypotheses outlined in the subsequent section were designed based upon prior research, as well as the theoretical tenets of social cognitive theory (Bandura, 1986).

Self-efficacy, Interest, and Identity

According to Bandura (1986), perceived self-efficacy can operate as a principal contributor to students' academic progress because individuals assume an active role in their motivation. Motivation has been found to have a mediating effect between self-concept and achievement, as well as self-efficacy and achievement. As an extension of Bandura's work, Deci and Ryan (1995) posited that students with higher motivation have more interest, resulting in better performance, persistence and creativity, higher vitality, higher self-esteem and well-being.

Parental Involvement

According to researchers (Hara & Burke, 1998; Hill & Craft, 2003), parental involvement in a child's early education is positively associated with academic achievement. Higher levels of academic performance have been found when parents are involved in their child's education (Mandara, Varner, Greene, & Richman, 2009). The significance of parental involvement on academic achievement for students has also been noted among policymakers with an objective to improve parent involvement through wider educational policy initiatives (Howard & Reynolds, 2008). Based upon prior theory and research, the following hypotheses are offered:

H1: Mathematics self-efficacy is a stronger predictor of STEM achievement in algebra than mathematics interest for female high school students

H2: Mathematics self-efficacy is a stronger predictor of STEM achievement in algebra than mathematics identity for female high school students

H3: Mathematics identity is a stronger predictor of STEM achievement in algebra than parental involvement for female high school students

H4: Parental involvement is a stronger predictor of STEM achievement in algebra for black female high school students, than those for other races

Significance of the Study

Although there has been reluctance in the past to rely on large datasets for dissertations, recent consensus is that a need exists for a critical mass of U.S. educational researchers to use large-scale datasets for basic, policy, and applied research (AERA, 2014). Therefore, existing data from a large-scale secondary source, The High School Longitudinal Study of 2009/2012 (HSLS:09/12) will be used for this research to examine academic and non-academic factors related to female high school student achievement in STEM courses. Data from HSLS:09/12 are longitudinal; therefore, significant findings may provide insight into the STEM course and career decisions of female high school students, as well as inform future policy or professionals regarding the need to enhance STEM motivation for underrepresented female students.

Operational Definitions

The following definitions, accompanied with citations, provide a succinct understanding of the terms used throughout the dissertation:

1. Black: In this dissertation, the term Black will be used to identify students who self-selected their race as Black/African American on the HSLS:09/12 survey.
2. Efficacy: "The power to produce an effect" (Merriam-Webster, 2014).
3. Minorities: A subordinate group with members who have considerably less command over their own lives when compared to members of a dominant group. This subordinate group is also known to experience disproportionately fewer opportunities (education or success) compared to the majority, their counterparts

(Schaefer, 1993; 2011). In this dissertation, the term minorities will be used when referring to race or ethnicity.

4. The Pygmalion effect: According to the Greenwood Dictionary of Education (2011), the Pygmalion effect is considered to be synonymous with self-fulfilling prophecy. In the field of education, the term implies a significantly strong link between teacher expectations and student outcomes.
5. Race: “As an essentially contested concept, ‘race’ has no fixed, essential meaning and is thus subject to multiple definitions” (Oh, 2009, p.1027). Therefore, it is important to note that race will be referred to in this dissertation as socially constructed racial or ethnic identities. Terms such as Black, White, and Hispanic are used specifically in chapter 4 of this dissertation based upon prior research and the terms used in the HSLS:09; however, APA guidelines now suggest using African American, European American, and Latino/a.
6. Self-concept: A self-perception that influences behavior.
7. Self-efficacy: Self-Efficacy is the personal conviction that an individual has about their own ability to achieve a goal or favorable outcome (Reeves, 2011).
8. Socio-economic status (SES): Generally conceptualized as the social position or class of one person or a group of individuals, measurable through a composite of income, education and occupation (APA, 2014).
9. STEM Pipeline: STEM is an acronym for Science, Technology, Engineering, and Mathematics. Use of the term STEM Pipeline refers to the flow and management of students into STEM courses and careers throughout K12, post-secondary, and beyond.

10. Stereotype Threat: “Stereotype threat is an occurrence whereby certain groups of people are affected by an unconscious fear of confirming a negative stereotype concerning their performance in a particular domain” (Ganley, et al., 2013, p. 1887).
11. Underrepresented: According to the Merriam-Websters dictionary, underrepresented means inadequately represented. In this dissertation, the term underrepresented will be used when referring to racial or ethnic disparities. Additionally, the term will be used when including other insufficiently represented populations in various academic settings, such as women.
12. White: In this dissertation, the term White will be used to identify students who self-selected White as their race on their completed survey.

CHAPTER TWO: Literature Review

The achievement gap in K-12 education has been extensively documented (Chubb & Loveless, 2002). According to the National Assessment of Educational Progress (NAEP, 2011), achievement gaps occur when one group of students outperforms another group and the difference in average scores for each group is statistically significant. This phenomenon has existed since the beginning of aptitude and achievement testing (Armor, 2005) . Today, African Americans, Latino/as, Native Americans, and certain sub-sets of Asian Americans are still largely underrepresented among high-achieving students (NAEP, 2010). NAEP (2010) researchers provided information on differences in achievement, revealing several unmet goals for minority students and confirming the persistent existence of a gap in achievement. Unmet goals include disparities in STEM achievement.

Despite a plethora of policy and school reform initiatives that have sought to reduce the achievement gap between European Americans and minorities, little sign of dissipation exists (Howard, 2010). When discussing the academic achievement gap, the term *minority* often refers to African Americans. This relationship can be attributed to the existence of disparities between European Americans and African Americans throughout much of the history of the United States (Williams, 2011), such as court cases like *Plessy v. Ferguson* (1896) and *Brown v. Board of Education of Topeka* (1954). The *Brown v. Board of Education* case generated an abundance of research on school racial compositions and student academic outcomes (Brown-Jeffy, 2009). Although African Americans traditionally represented the largest minority population in the U.S. (Carpenter

Ii, Ramirez, & Severn, 2006), the term *minority*, as used in this literature review, refers to African American, Asian American, Latino/a, and Native American students.

Bearing in mind the differences between and within minority groups, a confluence of factors associated with the academic achievement gap and differences in achievement exists. Research indicated that low achievement is related to certain family factors, such as socioeconomic status (Armor, 2006; Brooks-Gunn, Klebanov, Smith, Duncan, & Lee, 2003; Mandara et al.,, 2009), parents' IQ (Armor, 2006), parents' education (Byrnes, 2003), as well as limited family involvement in schools (Beckert, 2008; Jeynes, 2003). The Equal Educational Opportunity Report, commonly referred to as the Coleman Report (Coleman et al., 1966), revealed data supporting the assertion that family risk factors are so strong that achievement differences will persist, no matter what is done in schools. Data over a 50-year period, from the Coleman Report to the 2008 National Mathematics Advisory Panel (NMAP) report, indicated that the most significant variable related to achievement was the students' family background (Ornstein, 2010). As quantitative studies of school effects have generally supported the belief that the cause of the U.S. education dilemma lies outside of the school, further research indicated that school factors may also be linked to the achievement gap (Campos, 2008). According to Wenglinksy (2004), the effects of classroom practices are analogous in size to those of family background, implying that teachers can significantly impact student learning as much as the students themselves.

The purpose of this review is to provide a background for this research by contextualizing the literature on the gaps in achievement and the disproportionate representation of minorities, specifically females, in Science Technology Engineering and

Mathematics (STEM) related courses and careers. In order to effectively examine the literature, it is important to give attention to the history of STEM, followed by the seminal work of James Coleman (1966) on the achievement gap. Providing a brief overview of the history of STEM provides a contextual understanding of the need for more research on STEM and high school females. A brief synopsis of the Coleman Report provides insight into why the subsequent research on gaps in achievement are often divided by family and school risk factors. Therefore, the literature related to family and school factors are discussed to address parental involvement and the achievement differences between students. The motivational factors related to achievement are also included in this literature review, to provide context for the variables chosen to represent motivation as a predictor of STEM achievement. As a final point, the disparities in STEM achievement for females are outlined.

A Brief Overview of the STEM Crisis

In response to the national demand for qualified engineers and railroad/road designers to build infrastructures, the United Stated Military Academy at West Point was established in 1802 (Jolly, 2009). The Morrill Act was enacted later in 1862 to support colleges and universities with STEM related academic programs. The United States invested more time, energy, and funding in the sciences after the launch of Sputnik, a Soviet satellite, in 1957. In response to the United States' efforts to compete globally in the sciences, the National Defense Education Act was established in 1958 and the federal government dedicated one billion dollars towards STEM education reform (Jolly, 2009).

Efforts to address the national STEM crisis continue to be made by federal, state, and local organizations. In 2009, President Obama launched the *Educate to Innovate*

initiative with the goal to move American students' rankings in STEM achievement by 2020 (The White House, 2010). According to President Obama, America's future prosperity relies on STEM education. In response to his call for action, the Administration made STEM a priority as part of their $4 billion Race to the Top (RTT) competition. Although the Committee on Science, Engineering, and Public Policy (CSEPP) initially expressed an urgency to address the state of STEM education, secondary schools are not yet able to produce enough students with the interest, motivation, and skills required to compete and thrive (2007, CSEPP). The Administration pushed the agenda forward and encouraged the development of comprehensive strategies to improve STEM achievement through partnerships with local institutions. Additionally, strategies to increase the participation in STEM by women and underrepresented minorities were encouraged (The White House, 2010). According to Hill, Corbett, and Rose (2010), there needs to be an increase in the numbers of female students enrolling, persisting, and graduating in STEM fields. If the United States plans to meet the industry demand for more qualified STEM professionals, meeting this need is important.

Females historically have been underrepresented in STEM fields. Although the numbers of females in STEM majors have increased, at the undergraduate and graduate levels gender gaps persist (Morganson, Jones, & Major, 2010). Furthermore, the US Department of Commerce asserted that females hold fewer that 25% of STEM positions (Beede, Julian, Langdon, McKittrick, Khan & Doms2011). In 2009, the percentage of females in the workforce reached 49%; however, their rate of participation specifically in the STEM fields remained lower than their male counterparts (US Department of

Commerce, 2009). In 2012, the White House Council on Women and Girls addressed President Obama's challenge to emphasize teaching girls math and science, through public awareness campaigns. Later in 2012, the Obama Administration also influenced the STEM Master Teacher Corp initiative.

There is still confusion on which factors affect persistence in STEM for female students. The focus for future initiatives should be placed on ways to improve persistence; there is a need for further research to support policy directions for improving the overall participation of females in STEM. Although there has been growth in pathways for females to have access to advanced math and science courses in high school, females fail to achieve equal representation in undergraduate STEM studies careers. Researchers have studied multiple contributing factors related to academic preparation for females (Ethington & Wolfle, 1988). The obstacles related to academic achievement include perceptions of a lower self-assessment of capabilities for females compared to their male counterparts (Betz & Hackett, 1983; Brainard & Carlin 1998; Correll, 2001, 2004; Feather, 1988; Hyde, Fennema, & Lamon, 1990; Sax, 1994), societal stereotypes (Entwisle et al., 1994), a lack of female role models in STEM (Hill, 2010), as well as family and peer influences (Ost, 2010). The research on why females have a lower persistence in STEM majors has focused on academic preparation, self-confidence, self-efficacy, interest, identity, and parental involvement.

The Gender Gap in STEM

Researchers have analyzed longitudinal data from national, regional, and institutional databases and found positive correlations between success in college level STEM courses and high school GPA, as well as scores from the Scholastic Aptitude Test

(SAT) and American College Testing (ACT). In summary, researchers found that courses taken in high school are predictors of STEM achievement/advancement for students. For example, advanced level and AP math and science classes in high school were predictors of success in STEM majors and degree completion (Griffith, 2010). Bettinger (2010) reported results on the relationship between the highest ability math students based on ACT scores, indicating that after taking the highest level of courses women were 9-14% less likely to remain in STEM majors than their male counterparts.

Researchers (Tyson, Lee, Borman, & Hanson, 2007) conducted longitudinal research in which they followed approximately 100,000 Florida public high school students in the 11th and 12th grades through their undergraduate studies. Tyson et al. (2007) found a high correlation between STEM degree completion and the completion of advanced levels of high school math and science courses. Furthermore, females represented more than 50% of the high school graduates, with 21.5% of them receiving college degrees compared to 14.5% of male students. However, male students outnumbered female students 2 to 1 in the area of STEM degrees earned.

The gender gap in earned STEM degrees has persisted over the years (Chen & Weko, 2009; Huang, Taddese, & Walter, 2000; Schneider, Swanson, & Riegel-Crumb, 1997). The differences in math achievement scores between male and female students begin to appear in the 13 to 16 year age range, critical high school years (Halpern, 1986; Modi, Schoenberg, & Salmond, 2012). Modi et al. (2012) surveyed middle school-aged females and found that out of the 81% of participants who expressed some interest in a STEM career, 13% selected STEM as their first choice. Out of the 13% who selected STEM as their first choice, 67% selected the health care field. In 2009, the U.S.

Department of Commerce Economics and Statistics Administration Census reported that more than half (54.7%) of college graduates were female. In 2011, the U.S. Department of Education reported that since 1998 the number of females enrolling in college has exceeded the number of males. However, females earned less than 15% of the degrees in STEM fields compared to 87% of their male peers (Siebens & Ryan, 2012).

Academic achievement in higher-level math and science courses in secondary education has not answered the question of why women do not pursue STEM majors and careers (Bettinger, 2010). Researchers have indicated that a strong correlation exists between the selection of higher-level mathematics and science courses, and the subsequent selection of a STEM major (e.g., Nagy, Trautwein, Baumert, Ko˙ller, & Garrett, 2006; Watt, 2006). High school students may self-select mathematics and science classes perceived as important for majoring in the subject linked to their career aspirations. Self-selected courses are occasionally based on inaccurate information, which can lead to a premature elimination of STEM career options (Bargel, Multrus, & Schreiber, 2008; Poglia & Molo, 2007). Although advanced math and science courses are high school pre-requisites for success as a STEM undergraduate major, completing these courses does not guarantee that a female student will pursue a major or career in a STEM field. An isolated examination of achievement in high-level math and science does not address the existence of additional factors that may influence STEM achievement for female high school students.

Identity and Gender Stereotypes

Researchers have found that the enrollment in high-level mathematics courses was strongly correlated with mathematics performance and self-concept (Marsh & Yeung,

1997; Nagy et al., 2006). The subject-specific self-concept of females may very well be negotiated by self-image. The more the self-image resembles that of a typical student who likes the subject, the stronger the preference for the subject (Hannover & Kessels, 2004; Kessels, Hannover, & Rau, 2006). Stereotype threat for females in STEM is linked to the idea that women underperform in part due to a concern that their performance might confirm negative stereotypes about their group (Kiefer & Sekaquaptewa, 2007; Nosek, Banaji, & Greenwald, 2002; Schmader, 2002). According to Settles, Jellison and Pratt-Hyatt (2009), females often seem to acquiesce to stereotype threat and experience a conflict between their identity as a woman and their identity as a scientist. As females engage in gender stereotype endorsement, they are also viewing low percentages of women in STEM majors and careers, which may trigger an identity conflict (Bonnot & Croizet, 2007; Delisle, Guay, Senécal, & Larose, 2009). Researchers have identified additional factors that may also influence the STEM achievement and successful course and/or career selections for females, such as persistence and parental support.

Persistence in STEM and Parental Support

Researchers have conducted longitudinal studies and found that the interest in STEM careers for females decreased between 7th and 12th grade (Larose et al., 2008; Seymour, 1995; Van Leuvan, 2004). Furthermore, the gender stereotypes held by parents moderately influenced females' self-perceptions and experiences, and promoted gender-based career choices (Jacobs, Chhin, & Bleeker, 2006). Conversely, females with STEM career aspirations were raised in an academic environment and had parental role models in STEM fields (Packard & Nguyen, 2003). When considering parental involvement, it is

important to acknowledge that it is one of several components under the umbrella of family factors known to influence achievement.

Family Factors and Achievement

Researchers have contended that family factors such as socioeconomic status (Brooks-Gunn et al., 2003; Mandara et al., 2009; Orr, 2003), parents' education (Byrnes, 2003), parents' IQ (Armor, 2006), parental involvement (Jeynes, 2003), and parenting practices (Jeynes, 2007), explain the differences in academic achievement among students. A visible relationship between family risks and achievement may be noticeable as early as kindergarten, and through elementary and secondary education (Rathbun, West, & Walston, 2005). Studies have been conducted examining the relationship between academic achievement and other factors, such as economic resources, parental education, grandparent's education, household size, attitudes and values, child's birth weight, and parenting practices (Phillips, Crouse, & Ralph, 1998). Orr (2003) contended that as students become older, they become more aware of family factors. Older students are more likely to be exposed to the daily detriments of an impoverished community, unstable home conditions, and disproportionate occurrences of violence or death; all of which are known to have a significant impact on achievement (Duncan-Andrade, 2009; Howard, 2010).

The Coleman Report

In 1966, Coleman et al. examined student achievement in the U.S. using a sample size of approximately 650,000 students and teachers from nearly 4,000 different schools, with some intentional overrepresentation of schools with minorities. Congress commissioned this study in the Civil Rights Act of 1964 as one of the first social

scientific studies that would inform policy research in education (Nichols, 1967). Coleman et al. (1966) collected data on students' attitudes and family background, variations of resources available between school and among students, as well as measurable student achievement. Analyses of the data focused on four main areas: (a) segregation of minority groups in public schools, (b) inferiority of minority school facilities, (c) minority variance on school achievement tests and (d) the extent of disparities in academic achievement for minorities with varying educational opportunities. The results of the study, documented in the Coleman Report, found a gap in academic achievement between European Americans and minorities (Coleman et al., 1966). Whereas there were variations in the quality of school resources, differences in a student's family background were significantly associated with academic achievement. The Coleman Report (1966) regarded schools only as effective as the surrounding society, with academic achievement reliant on circumstances beyond school control. According to Coleman et al. (1966):

> Taking all of [the] results together, one implication stands out above all: That schools bring little influence to bear on a child's achievement that is independent of his background and general social context; and that this very lack of an independent effect means that the inequalities imposed on children by their home, neighborhood, and peer environment are carried along to become inequalities with which they confront adult life at the end of school (p. 325).

Nichols' (1967) review of the Coleman Report maintained that the study was costly at $1.25 million and "hastily put together to meet a two-year congressional deadline" (p. 528). The two-year timeframe only allowed for certain communities and

schools to participate in the surveys; the data made available accounted for only 59% of the sampled schools. Coleman et al. were also criticized for their exclusion of student names, because it prohibited future retesting that could have generated data for a longitudinal study extending from first through twelfth grade. Furthermore, researchers (Gamoran & Long, 2006) argued that the Coleman study's cross-sectional design did not adequately capture causal effects. The study suffers from limitations common to non-experimental studies attempting to measure the effects of natural experiments, leaving uncertainty as to whether correlations would hold if the variables were manipulated; the conclusion of the study was an example of interpreting correlation as indicative of causation (Gamoran & Long, 2006). Whereas critics asserted that limitations detract from the significance of the study, the Coleman Report continues to influence research on school effects, as well as family risks and the relationship of SES to academic achievement (Gamoran & Long, 2006; Howard, 2010).

Socioeconomic Status

The relationship of SES to academic achievement has become a more complex issue over the years, and it can be examined on various levels (Howard, 2010). Conflicting research exists on the strength of the relationship between a student's SES and their academic achievement (Duncan-Andrade, 2009; White et al., 1993). Some researchers (Mandara et al., 2009) examined data based on aggregate measures of SES and student achievement, confirming Coleman's assertion that students from low SES backgrounds achieve less than students from high SES backgrounds. White et al. (1993) examined two data sets, one at the individual level where SES was determined by whether students obtained free or reduced price lunch, and another at the aggregate level

by percentage of students receiving the same lunch. A linear regression was conducted for each student (individual and aggregated), with student achievement as the dependent variable. The researchers concluded that the aggregate level data overestimated the percentage explained by SES at 72% of the variance in achievement levels, and using individual student data accounted for less than 20%. This difference was also noted by Mandara et al. (2009) in an examination of intergenerational family predictors of achievement gaps. The results of their study showed that the minority gap in achievement and SES had reduced considerably over the years; however, economic differences continued to advantage those from higher SES backgrounds.

The association between school SES, student race and SES, and academic performance has been a focal point when discussing the achievement gap (Armor, 2005; Desimone & Long, 2010; Howard, 2010). Economic differences arguably explain the academic disparities in achievement between European American and minority students from low SES backgrounds who have limited access to resources, which can possibly impact academic achievement (Howard, 2010). Research data from the National Longitudinal Survey of Youth (NLSY) were used by Orr (2003) to examine the possible impact of economics on the achievement gap. The subset of NLSY data used by Orr included approximately 3,000 women between the ages of 14 and 21.

Academic achievement was the dependent variable in Orr's analyses, as measured by standardized scores on the Mathematics subscale of the Peabody Individual Achievement Test (PIAT). The Mathematics subscale was determined to be a valid and reliable assessment, with a test-retest reliability range of 0.73 (for 5th graders), 0.83 (for 12th graders), and an across-grade median of 0.74. The independent variables in the

analyses were net worth, SES, and race. Cultural capital, educational resources in the home, social capital, child self-esteem, and school quality were the mediating variables. Orr (2003) posited the following hypotheses:

> Hypothesis 1: After parental education, occupation, and income are controlled, parental wealth will have a positive effect on a child's achievement.
>
> Hypothesis 2: The effect of wealth on achievement will increase as a child grows older.
>
> Hypothesis 3: Wealth in the form of income-producing assets will have a greater effect on achievement than will wealth in the form of non-income-producing assets.

Orr used ordinary least-squares (OLS) regression to test the above hypotheses and found that wealth had a positive affect on a child's academic achievement, after controlling for SES. Additionally, Orr indicated that there was no significant difference in the impact of wealth based upon the age of a child. Orr's analyses did not fully address the widening racial gap (in test scores), as students progressed through school. Older children are often more aware than younger children about household financial obligations, making them more likely to be concerned about educational resources and expenses (Duncan-Andrade, 2009; Orr, 2003).

Parents in low SES households are less likely to have the ability to financially contribute to the education of their children (Orr, 2003). SES may also be considered a stronger predictor of achievement for older students, because more resources are needed

to manage a higher level of academic rigor (Howard, 2010). Further research indicated that minority students with low SES backgrounds are less likely to have received proficient grade marks in school than their wealthier European American counterparts, regardless of age (Mickelson, Bottia, & Southworth, 2008).

Mickelson et al. (2008) examined disaggregated test scores by poverty level of schools and the students' individual SES and race over a two-year period. The results of their study also revealed an association between school SES and academic achievement, regardless of students' age or individual SES. Similar results were discovered by Chall (1996) in a study that analyzed NAEP results and Scholastic Aptitude Test (SAT) scores from 1910 to 1996. Students who attended low SES schools performed worse than students similar in race who attended wealthier schools (Chall, 1996; Mickelson et al., 2008). Whereas SES at the individual student level is a predictor of academic achievement, the correlation to the school level is stronger (Sirin, 2005).

Family SES typically determines the school to which a student has access (Reardon, Yun, & Kurlaendor, 2006); the possible impact of family SES on achievement is minimized when neighborhood SES is taken into consideration (Sirin, 2005). In other words, the location of a school can determine the financial resources available for students, which can be linked to higher SES neighborhoods. This assertion was made by Unnever, Kerckhoff, and Robinson (2000) preceding an examination of data associating resources and school SES to academic achievement. The results indicated that the relationship between academic achievement and family SES varied for individual students based on minority status, residing neighborhoods, and the school SES (Unnever

et al., 2000). A further comparison of low SES schools to higher SES schools has also shown variance in parental involvement (Howard & Reynolds, 2008).

Parental Involvement and Achievement

The term parental involvement refers to parenting behaviors that are directly or indirectly linked to their child's academic achievement and cognitive development (Cheung & Pomerantz, 2012; Fantuzzo, McWayne, Perry, & Childs 2004). Three distinct characteristics of parental involvement are prominent in the literature: a) participation in schools; (b) communication between parents and schools; and (c) home educational activities (Epstein, 2005; Howard & Reynolds, 2008). Participation in schools typically refers to a parent's presence at school functions, their volunteer support, as well as Parent Teacher's Association (PTA) membership. Communication with teachers may include written correspondences via letter or email and/or phone calls. Finally, home educational activities typically pertain to parents assisting their child with homework or engaging in dialogue about the daily occurrences at school. Parental involvement can also include the emotional support given at home and a child's nutrition (Armor, 2006).

In 2005, Jeynes conducted a meta-analysis to determine the overall significance of parental involvement on academic achievement for K-12 students. Although Jeynes' initial search yielded 5,000 articles, 50 quantitative research articles that examined the relationship between parental involvement and urban elementary student achievement of which 41 were retained for analysis based upon the degree of sufficient quantitative data in each body of research, yielding over 20,000 participants.

Jeynes examined components of parental involvement to determine correlations to academic achievement. Three research questions were addressed: a) To what degree is

parental involvement associated with higher levels of school achievement among urban students?; b) Do school programs of parental involvement positively influence urban students?; c) What aspects of parental involvement help those students the most?; and d) Does the relationship between parental involvement and academic achievement hold across race and gender groups?

For question one, effect sizes that emerged were similar to those reported in studies on parental involvement (in general) that used elaborate controls, and the regression coefficients for these studies were .75 ($p < .01$) and .73 ($p < .01$), respectively. For studies without sophisticated controls, the effect size that emerged for GPA were .85 ($p < .001$), .40 ($p < .01$) for standardized tests, and .34 ($p = ns$) for other measures (Jeynes, 2005). Analyses that used controls had betas of .86 ($p < .0001$) for GPA and .21 ($p < .05$) for standardized tests.

For research question number two, the combined analyses related to parental involvement programs yielded an effect size of .27. The studies without elaborate controls yielded an effect size of .31 ($p < .05$), and for studies with controls the regression coefficient was .19 ($p < .05$). The academic measures examined without sophisticated controls yielded a high effect size for standardized tests at .40 ($p < .01$). The combined standardized tests yielded an effect size of .40. Parental expectations in the analysis for research question number three yielded the largest effect sizes for all components of parental involvement; the regression coefficient for overall achievement was .58 ($p < .05$).

In order to address question number four on parental involvement and achievement by race, the research articles were first separated into two groups: a) studies

with 100% racial minorities; and b) studies in which a majority (85%, on average) of students were a racial minority. For studies with a majority of students considered a racial minority the effect sizes for overall achievement were 1.06 ($p < .0001$) without elaborate controls and .84 ($p < .0001$) when sophisticated controls were used. The 1.06 effect size was larger than the effect size for students from White families ($p < .001$). There were no statistically significant differences when comparing mostly minority and mostly European American students when controls were in place. In studies with all students holding a minority racial status, the regression coefficients were .29 ($p < .05$) when no controls were used, and .46 ($p < .01$) for those with elaborate controls in place. All the effect sizes were one fourth of a standard deviation (or more). Unfortunately, Jeynes did not make comparisons with studies of all European American students. In summary, statistically significant effects emerged across multiple achievement measures (e.g., GPA, standardized test scores). The results from Jeynes' meta-analysis contain a range of statistically significant effect sizes that further support claims about a strong relationship between parental involvement and educational outcomes.

In a subsequent study, Jeynes (2007) indicated that two components of parental involvement had a significant relationship to higher academic achievement: (a) parental involvement as an investment of time; and (b) parental involvement related to parenting style and expectations. For minorities (such as African American and Latino students) the correlation between parental involvement and academic achievement tended to be greater than they were for Asian American children; however, the effect sizes were statistically significant for all three of these minority groups. Overall results indicated

that parental involvement was associated with academic achievement across racial groups (Jeynes, 2005).

Parenting practices, such as creating a school-friendly home atmosphere, have been linked to higher levels of achievement gap (Mandara et al., 2009). Parents with a strong sense of the effect of their present actions on future outcomes may be more likely to invest in their children's education than those who do not have this sense (Orr, 2003). Parents may be more likely to make financial investments in their children's education if they have an understanding of how important education is for their child's future. According to Orr (2003), relationships and interactions are another important investment for parents. This includes reading with their children, helping with homework, or participating in school activities. Parents who engage in these activities may also be more concerned about the quality of their children's school or the educational resources available to the children at home (Orr, 2003). This type of parental support can positively affect a child's academic achievement (Ornstein, 2010).

Bakker, Denessen, and Brus-Laeven (2007) studied parental involvement and teacher perceptions of parental involvement in relation to level of parental education and student achievement. The results indicated a weak relationship between teacher perceptions and parental accounts of their own involvement. The analyses also indicated a stronger relationship between teacher perceptions of parental involvement and student achievement than parental accounts. Additionally Bakker et al. (2007) suggested that the stereotypes of parents, by teachers, were also related to academic achievement (Bakker et al., 2007). Bakker et al. (2007) also examined the relationship between parental level of education, parental involvement and student achievement. The findings indicated that

parent and teacher accounts of parental involvement were also related to achievement scores for students.

Parent involvement in a child's education at early onset has been found to be positively correlated with a child’s academic achievement (Jeynes, 2007; Mandara et al., 2009). Students with parents actively involved in their education demonstrated higher levels of academic performance than students with less involved parents (Jeynes, 2007; Mandara et al., 2009). Parents involved in their child's education are able to positively encourage their child's academic achievement by: (a) supporting the child’s increased self-perception of cognitive competence and (b) engaging with the teacher and school to promote an influential student-teacher relationship (Bakker et al., 2007). The significance of parent involvement on academic achievement for students has been noted among researchers, as well as by policymakers (Howard & Reynolds, 2008).

School Factors

The Coleman Report indicated that family risk factors were so strong that differences in academic achievement would persist, regardless of what was done in schools. Quantitative studies of school effects supported this belief (Brooks-Gunn et al., 2003; Ornstein, 2010; Orr, 2003). However, other researchers argued that school factors may also be linked to the achievement gap (e.g., Campos, 2008). Although researchers have contended that negative relationships between family and school factors to academic achievement for minorities exist, the comparison of any group to European American students supports the notion that European American achievement is the standard for measurement. Furthermore, this comparison ignores the possibility of European American students under-performing. To better address ways to close the

achievement gap, researchers and educators need to focus on differences between these minority groups and European Americans, while also considering the existence of an achievement gap among European American students.

Despite policy and school reform initiatives that seek to reduce the achievement gap between European Americans and Minorities, there has been little sign of change (Howard, 2010). One of the potential problems with trying to determine factors associated with the achievement gap is that, depending on the nature of the factor, little may be done to change the situation (Williams, 2011). Whereas education researchers have argued that increases in student achievement can occur, limited research exists to confirm exclusive correlations to changes in family or school factors; causal explanations of the achievement gap have not been thoroughly examined. School and family risk factors should be considered when seeking new initiatives to narrow gap(s) in achievement. Factors such as economic challenges, parental involvement, motivational and emotional challenges of students should certainly be considered, as well as school factors.

Researchers have found that family risk factors correlate with the achievement gap, but some point out that the risk factors do not explain the entire gap (e.g., Armor, 2006). Gaps in achievement can also be associated with teacher expectations (Ferguson, 2003; Levitt & Fryer, 2004). Researchers contend that positive teaching expectations can make a difference in academic achievement, and that teachers play a valuable role in the academic achievement of students (Howard, 2010; Trouilloud, Sarrazin, Martinek, & Guillet, 2002).

The role of the teacher may be to deliver instruction as well as encourage achievement through clear expectations (Trouilloud et al., 2002). A teacher's expectations may also be confirmed through a student's achievement as these expectations may create self-fulfilling prophecies, also known as the *Pygmalion Effect* (Trouilloud et al., 2002). In their classic study, Rosenthal and Jacobson (1968) led teachers to believe that a group of randomly selected students would likely progress academically. Teachers had higher expectations for the selected students than the control group. By year's end, students of teachers who held high expectations achieved more academic growth than students in the control group.

Research by Hughes, Gleason and Zhang (2005) found that intimate, encouraging student-teacher relationships were positively related to academic achievement. Desimone and Long (2010) further examined issues related to teachers and teaching, specifically their effects on achievement and inequality, asserting that schools play a significant role in addressing the achievement gap. The teacher quality aspects examined were: (a) degree in math, (b) experience, (c) certification, (d) math courses, (e) professional development, and (f) time spent on subjects. Desimone and Long (2010) specifically examined these data in the National Center for Education Statistics Early Childhood Longitudinal Study (2000). Their findings indicated lower achieving students were initially placed with basic instruction teachers and higher achieving students with teachers of more advanced instruction. Teachers of advanced instruction spent more time on the material included in standardized tests, whereas other teachers spent less time on test prep. In short, disadvantaged minority students received instruction unrelated to achievement growth (Desimone & Long, 2010).

Minority students are more likely to be assigned teachers who spend less time on standardized test subjects (Ferguson, 2003). Although Desimone and Long (2010) found that minority students tended to be assigned to teachers who spent less time on subject matter related to tests, they acknowledged that teacher and teaching quality may operate independently. Furthermore, the issue of low achievement may have more to do with the course placement of students than with the quality of the teacher with whom they are placed (Desimone & Long, 2010). Additionally, it is important to note that time on instruction can be a significant factor in academic achievement. A teacher's decision to spend less time on certain subjects may also be related to the attitude and expectations they have towards students in their classes (de Boer, Bosker, & van der Werf, 2010).

Motivation

As teachers have expectations of students, students have expectations and self-perceptions that may or may not contribute toward their success in mathematics and science courses. In this dissertation, the researcher examines achievement on two motivational constructs: self-efficacy, derived from self-efficacy theory, as well as interest (Bandura, 1997; Eccles, Adler, Futterman, Goff, Kaczala, & Meece, 1983). The motivational constructs selected for this research were appropriate for the current study because they are grounded in theories that acknowledge the role of the social context in influencing student motivation. Prior research that utilized these frameworks has also socially contextualized rationalizations for gender disparities in school attitudes, feelings, and choices (Wigfield & Eccles, 1992; Wigfield, Eccles, & Pintrich, 1996). Additionally, researchers have found in multiple studies that the selected constructs predicted academic persistence, effort, achievement, and choice (Bandura, Barbaranelli, Caprara, & Pastorelli,

1996).

Self-Efficacy

Self-efficacy theory seeks to explain the variance in student motivation. Self-efficacy refers to beliefs about one's ability to attain task and situation-specific outcomes (Bandura, 1997). Bandura asserted that when one feels competent in a given domain, he or she will be more motivated to approach tasks, put effort into them, and persevere when faced with challenges. Researchers have found that higher levels of self-efficacy predict academic effort, persistence, learning, achievement, course enrollment, and career choice (Bandura, 1997; Pajares, 1996; Pintrich & Schunk, 2002; Schunk, 1995; Schunk & Pajares, 2002). Four sources of information on self-efficacy are outlined under Social Cognitive Theory as follows: enactive attainments, vicarious experience, verbal persuasion, and physiological state (Bandura, 1986; 1997).

Enactive Attainments. Enactive attainments refer to the effects of experiences on efficacy - prior success can elevate efficacy while prior failure can lower efficacy. Before an individual can judge their self-efficacy several factors must be balanced, such as ability, non-ability, achievement success/failure, effort, and task difficulty. The manner in which individuals monitor their own performances is another attribute that may impact an individual's self-efficacy. For example, if an individual chooses to focus on positive performance then the potential to increase perceptions of their self-efficacy exists, and the same would be true for the reverse. According to Bandura (1986), mastery experiences are the most effective way for an individual to develop a strong sense of self-efficacy.

Vicarious Experience. Vicarious experience, on the other hand, tends to have an overwhelming influence on individuals. This source of self-efficacy occurs with the

belief in one's own ability to achieve certain results after observing individuals similar to them who have engaged/succeeded in the same activity (Bandura, 1986; 1997). Observing the enactment and success of others can have significant influence on an individual's performance. According to Schunk, Pintrich, and Meece (2008), an individual observing successes, failures, rewards, and punishments of others may expect to experience similar outcomes through comparable behaviors. Furthermore, Bandura (1997) asserted that social comparisons are a fundamental feature of vicarious experience and affect the choice of models. Various strategies learned from these models, such as coping, can also help increase efficacy. Models are useful when learning more complex skills (Bandura, 1987). Additional research indicated that family models are also influential, especially for the academic success of African American students (Berry, 2008; Martin, 2000; Walker, 2006).

Verbal Persuasion. Verbal persuasion is used to convince people that they possess the necessary characteristics to achieve certain outcomes (Bandura, 1986; 1997). This source can influence the additional effort and perseverance needed to achieve desired goals, but first the person who is receiving the persuasion must deem individuals who provide verbal persuasion competent enough to do so. In an examination of the self-efficacy of women who had entered STEM careers, Zeldin and Pajares (2000) found that verbal persuasion was an essential source of their participants' self-efficacy. Cues from family, teachers, peers, and supervisors were received by the women in the study resulting in the belief in their own ability to succeed. Additionally, Nobel (2011) found verbal persuasion to be a critical source of self-efficacy. In his study of mathematics self-efficacy, he found that verbal persuasion from teachers encouraged African American

male students to engage in mathematics clubs that ultimately supported their academic success in this subject area.

Physiological State. Physiological state, the last of the four sources, provides arousal signals that are used by a person to infer their ability to achieve a particular outcome (Bandura, 1986; 1997). The inference is based on the individual's judgment, as well as factors such as past experiences. In other words, an individual may examine their own self-efficacy by how they perceive their anxiety level in different situations. An example of arousal signals and their impact on performance is apparent in stereotype threat (Steele & Aronson, 1995), which can affect the anxiety of underrepresented groups (minorities and females). Additional research has shown that the introduction of a stereotype can negatively influence mathematics achievement (Keller, 2007); reducing stereotype threat can elevate achievement (Kellow & Jones, 2008; Kiefer & Sekquaptewa, 2007; Ryan & Ryan, 2005). Stereotype threat may also influence students' interests and identity development in any given subject. According to Martin (2000), mathematics identity parallels racial identity.

Identity and Interest

In their work with the Search Institute on the developmental assets in youth, Scales and Leffert (2004) asserted that identity could best be defined "as an integrated view of oneself encompassing self-concept, beliefs, capacities, roles, and personal history" (p. 193). According to this definition, identity is a variable influenced by self and others. Identity is socially constructed and changes through interactions within different communities in which individuals live, work, and learn (Holland & Lave, 2001). Sfard and Prusak (2005), compared identity with stories that people hear and tell about

themselves; therefore, an individual's mathematics identity is most likely connected to the stories about their mathematics experiences.

According to Voss and Schauble (1992), higher levels of interest would result in higher levels of cognitive activation leading to higher achievement. A meta-analysis of 121 independent correlation coefficients between achievement and interest indicated an average correlation of .40, after correcting for attenuation (Schiefele, Krapp, & Winteler, 1992). Furthermore, researchers of longitudinal studies contended the significance of aiding interest in mathematics was to influence a student's commitment to learning and pursuing STEM careers (Chan et al., 2010; Heller & Perleth, 2008; Lubinski & Benbow, 2006). According to Hidi (2000) interest in academic courses typically decreases over time for students; this trend is more commonly seen in mathematics and science- related courses (Krapp, 2002).

Researchers have examined self-identity, mathematics identity, and interest in relationship to achievement in mathematics (e.g., Hackett & Betz, 1989; Martin, 2000). Identity and interest are important constructs that can inform how students enact norms, beliefs, and characteristics of mathematicians and how they engage with mathematics related content and/or careers. Additionally, advocates of the identity and interest constructs have contended that these factors allow researchers to broaden the scope of analysis related to achievement to consider why students commit to and value content material (e.g., Cobb, Gresalfi, & Hodge, 2009). Although there has been an emerging interest in identity as a construct for understanding students' choices and behaviors in relation to STEM coursework and careers, it has yet to become a sustained quantitative research focus (Carlone & Johnson, 2007). In summary, motivational theories are

appropriate for this research in relation to gender and race differences in STEM achievement.

Disparities in STEM

As noted in the research discussed in this literature review, there are multiple factors to consider when considering gaps in academic achievement. Gaps in achievement have been identified in various academic areas, including STEM disciplines. As noted previously, STEM is an essential component related to the growth and development of the United States (ESA, 2011; Legewie & DiPetre, 2011; Reiss, 2012). Increases in educational achievement also contribute to the growth and well-being of the nation (Emdin, 2011). The racial minorities that represent larger percentages of the populace may benefit from support and encouragement to pursue STEM courses. In order to meet the increasing demands of the workforces for more skilled workers, all populations must be fully engaged (Board of Science Education, 2011).

An increase in the numbers of jobs available and the growth of minority groups in the educational system may suggest a greater need to prepare minority students for STEM courses and the selection of STEM careers. Although the growth of minority groups would suggest their contribution to the STEM pipeline, there is an achievement gap that persists between racial minorities and non-minorities (Guyll, Madon, Prieto, & Scherr, 2010). A gap in achievement between racial groups further contributes to the underrepresentation of certain minorities and women in STEM courses (Board of Science Education, 2011; Cole & Espinoza, 2008). Efforts have been made to decrease the gap in achievement between males and females; however, the representation of females remains disproportionately low (Halpern, Bendow, Geary, Gur, Hyde, & Gernsbacher, 2007).

Halpern et al. (2007) reported that among U.S. doctoral degrees awarded to females in the U.S., 27% were in mathematics, 15% in physics, 20% in computer science, and 18% in engineering.

According to the National Science Board (2012), women have historically been underrepresented in STEM fields. Blickenstaff (2005) argued that there are multiple factors contributing to gender disparity – some without merit and others that may contribute significantly to the removal of females from the STEM pipeline. One suggested issue attributed to fewer women in STEM is the nature of science itself. Some researchers (Landgraf, Peters, & Salmons-Stephens2008; Bix, 2004) argued that STEM has been a male-dominated field that females choose to avoid. A male-dominated environment may cause internal conflict for women who pursue a STEM career trajectory (Wylie, Jakobsen, & Fosado, 2007). Are females students in fact responding to the confrontation of gender-bias?

Research has indicated that women are faced with more issues than gender-bias in STEM. According to Robnett and Leaper (2013), other factors may include motivation-related self-concepts. Gender differences in interest and self-efficacy may significantly impact achievement, as well as female students' choices to pursue higher-level courses and/or careers in STEM (Halpern et al., 2007; Seymour & Hewitt, 1997). In a study by Simpkins and a team of researchers (2006), it was determined that girls were more likely to be negatively influenced by lower grades in middle school and high school than their male counterparts. Gender differences in self-efficacy begin to emerge during middle school as well (Fan, 2011). For instances when girls performed similarly to boys in math and science grades, boys still tended to score higher than girls in ability beliefs and value

regarding math and science (e.g., Eccles et al., 1993; Else-Quest, Linn, & Hyde, 2010). Academic achievement is an essential component of sustained interest and motivation to persist in any given domain. Understanding gender-related differences in motivation, such as self-efficacy, interest, and identity, may support in identifying future disparities in STEM achievement (Halpern et al. 2007).

In addition to gender-related disparities, researchers have found that discrepancies in female motivation and achievement may be more prevalent in those who also deal with racial/ethnic bias (Gonzalez, 2006; Guyll, Madon, Prieto, & Scherr, 2010; Steele, 1996; Wylie et al., 2007). Gonzalez (2006) conducted a retrospective study on Latina doctorates and found that women were advised, directly or indirectly, that they needed to work twice as hard and be twice as good to survive in their doctoral programs. Herein lies the gap in the literature – limited research exists related specifically to motivation and STEM achievement for underrepresented females.

Conclusion

Although researchers have suggested that gaps in achievement are beginning to narrow, they persist for females. STEM fields continue to grow, as does the need for a greater representation of underrepresented groups within the discipline. Due to the reported disparities in female achievement and motivation, it is evident that further research may contribute to the literature and potentially inform future policy and/or practice. In a society where claims are made about job shortages, one would be remiss not to consider better practices for preparing a growing population of students. Motivating underrepresented females to succeed in STEM courses should not imply that

they will select STEM careers; however, more options will be available for their future course or career trajectory.

CHAPTER THREE: Methodology

According to the literature in the field, positive STEM experiences are related to factors reflecting higher interest, identity, and self-efficacy in math and science. Additionally, an observable relationship between socioeconomic status and academic performance in math and science has been found to exist among high school students. Prior research results imply that the higher the level of socioeconomic background and parental involvement, along with higher interest and self-efficacy, the higher a students' academic performance. Furthermore, the differences between male and female high school student performance in STEM courses have been documented (e.g., Leaper, Farkas & Brown, 2012). Thus, it is important to separate the above factors to understand potential predictors of academic achievement for female high school students.

As stated previously, the purpose of this research is to identify the disparities associated with STEM achievement in algebra for female high school students. Considering academic (e.g., grades and assessment scores) and non-academic factors (e.g., socio-economic status and efficacy) may provide insight into the achievement of female high school students, specifically in mathematics and science. The dataset in this research is from the High School Longitudinal Study of 2009/2012 (HSLS:09/12). The HSLS data are used to examine levels of self-efficacy, interest, identity, and parental involvement as predictors of achievement for female high school students in STEM fields. For the analyses, female students were extracted from the full dataset. Hierarchical Multiple Regression (HMR) was then utilized for the data analysis, and the results are discussed in the findings section of this dissertation.

NCES Secondary Longitudinal Study

NCES instituted the Secondary Longitudinal Studies Program in response to the need for statistics and data on the state of education in the United States, as well as for policy-relevant, nationally representative samples of high school students. The purpose of the NCES Secondary Longitudinal Study Program (SLSP) is to evaluate students' educational, vocational, and personal development at different phases of their educational careers. Additionally, the program aims to study the personal, familial, social, institutional, and cultural factors that may affect the students' development. The ultimate goal is to provide "bases for further understanding the correlates of educational success in the United States" (Ingles et al., 2011).

The SLSP program includes the following three completed studies: a) the National Longitudinal Study of the High School Class of 1972 (NLS:72); b) the High School and Beyond (HS&B) longitudinal study of 1980; and c) the National Education Longitudinal Study of 1988 (NELS:88). The program also contains the base-year, first, and second follow-up data for the Education Longitudinal Study of 2002 (ELS:2002). ELS:2002 data for the third follow-up (2012) are in preparation for release. The High School Longitudinal Study of 2009 is the fifth study in the SLSP program. Considering the time span covering the collection of data for the above longitudinal studies, the educational experiences of students have been documented over four decades – beginning in the 1970s (Figure 1).

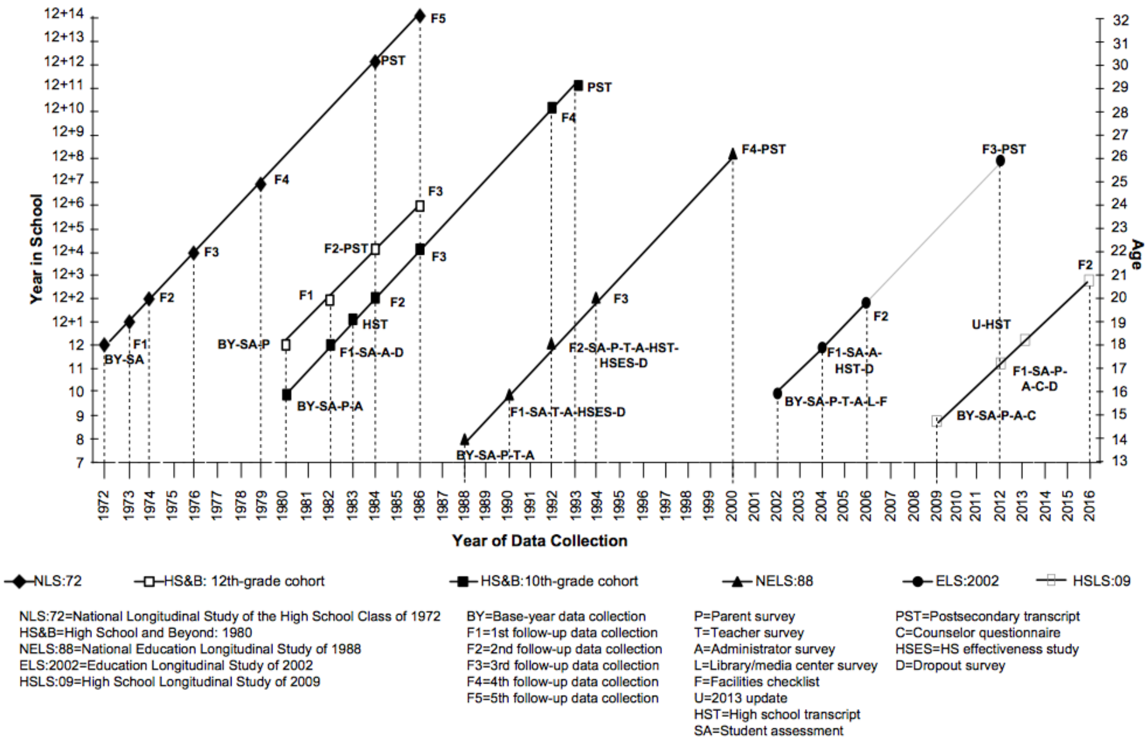

Figure 1: A temporal representation of the five longitudinal education studies in the SLSP for the time frame 1972–2016 (the next follow-up release).

High School Longitudinal Study of 2009/2012

Specific data for this research were selected from the HSLS:09/12 to aid in the examination of the achievement and motivation of female high school students. There are benefits to using a large database, such as time and cost efficiency. Most notably, the scale and availability of the data collected in large datasets build a strong case for the inclusion of the HSLS:09/12 as a data source in this research; however, there are limitations to consider. For example, due to their non-randomization and the potential covariates that may influence findings (e.g., multiple dates of test administration) national datasets often present challenges to making causal inferences.

The data from the HSLS:09/12 include results from a study-administered assessment, surveys, and data banks collected prior to this research project, yet available

at no cost to researchers. Although there has been reluctance in the past to rely on large datasets for dissertations, recent consensus is that a need exists for American educational researchers to use large-scale datasets for basic, policy, and applied research (AERA, 2014). Additional critiques for using existing datasets are directly related to which data are selected for certain research efforts and the analysis of said data.

The HSLS is conducted by the U.S. Department of Education's National Center for Educational Statistics (NCES) and focuses on understanding students' trajectories from the beginning of high school into postsecondary education and beyond. The data come from a random sample of more than 21,000 students from 944 public, charter, and private schools in the United States. In 2009, the base year participants (in ninth grade) completed a mathematics assessment in algebraic skills, reasoning, and problem solving. Additional data were collected via phone and online surveys administered to the students, parents, math teachers, science teachers, school administrators, and counselors.

The first follow-up data from the HSLS:09 were collected in the spring of 2012 when most participants from the sample were in their 11th grade year. Similar to the base year, participants completed an online survey about their educational expectations, math and science efficacy, and plans for postsecondary education. Both waves of data collection included a mathematics assessment of algebraic reasoning and a computer-based survey related to various psychological and motivational constructs (Ingels, Dalton, Holder, Lauff, & Burns, 2011; Ingels,et al., 2014). Data were selected to aid in the examination of the relationship between STEM performance, motivation, and parental involvement for female high school students. Additionally, student data were collected related to gains since the 9th grade. This dissertation reports on the first follow-up data

collected during the 2011-12 school year. Data for the 2013 update are in collection, collection of High School Transcripts (2013-2014) will begin in the fall of 2014, and a release of data for the second follow-up is planned for 2016. The longitudinal design of HSLS:09/12 is detailed in Figure 2.

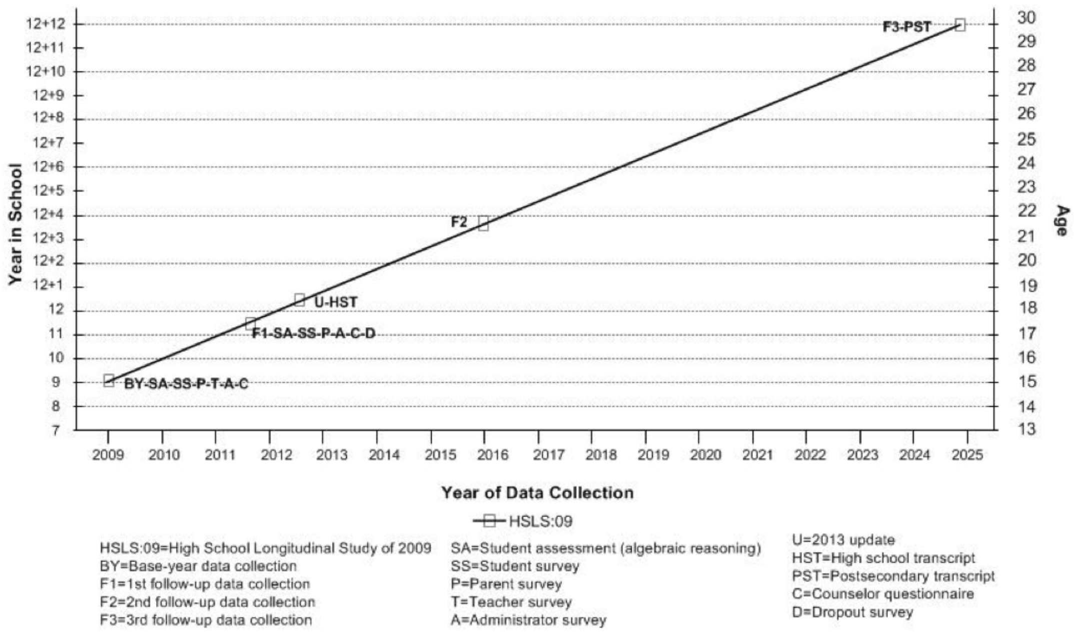

Figure 2: Longitudinal design of the HSLS:09/12 9th grade cohort from 2009 to 2021.

The base-year and first follow-up studies were conducted through a contract to RTI International, a university-affiliated, nonprofit research organization in North Carolina. RTI worked in collaboration with the following subcontractors: the American Institutes for Research, Horizon Research, Windwalker, and Research Support Services. The HSLS:09/12 dataset has been produced in both public-use and restricted-use versions. This dissertation used the publicly released data, which minimizes the risk of disclosing the identity of responding students, teachers, counselors, and administrators.

HSLS Research and Policy Implications

The HSLS:09/12 addresses similar concerns as the longitudinal studies that precede it from NCES' Secondary Longitudinal Study Program. Those issues include students' transitions from high school to postsecondary education and beyond. Additionally, the HSLS:09/12 focuses more specifically on the transition of youth through the paths that lead students to pursue and persist in STEM courses and careers.

According the NCES (2011), researchers who examine the data in the HSLS:09/12 follow-up will be able to measure mathematics achievement gains in the first 3 years of high school. The relationships among tested achievement, choice, access, and persistence can be measured as well. Additionally, the HSLS:09/12 mathematics assessment is as an outcome measure and a predictor of a student's ability to advance in STEM courses and careers. The study began with fall ninth-graders, and it identifies high school dropouts in the first follow-up wave.

The study questions students on decision-making processes for high school courses and their postsecondary trajectory. Students are also asked about the factors that influence the decisions about courses and careers, including factors related to parental involvement and financial aid. The questionnaires focus on the students' motivational factors related to their pursuit and persistence in STEM courses and careers. In summary, data in the HSLS:09/12 allow researchers, educators, and policy-makers to evaluate motivation, achievement, pursuit, and persistence in STEM courses and careers for youth.

Variables and Scales

The content of the student survey included future positioning and other substantive questions (Ingles et al., 2011). The survey obtained demographic information

(e.g., sex, race/ethnicity, income), language background, as well as school experiences in the current and previous school years. The researchers of the HSLS:09/12 survey conducted principal component analysis to develop scales from the student questionnaire responses (Ingles et al., 2011). The surveys contained separate scales for mathematics and science. The following scales in mathematics are used in this dissertation: a) self-efficacy; b) interest; and c) identity. Each of the above three scales were standardized to have a mean of 0 and standard deviation of 1. Scale values were assigned to participants who provided an entire set of responses. A parental involvement scale was created for this dissertation, as one was not provided in the HSLS: 09/12. A socio-economic status composite variable was used as the control variable in this dissertation, and the Mathematics Theta Score was used as the dependent variable. All of the variables used for this dissertation are outlined in Table 1.

Self-Efficacy

Self-efficacy signifies the students' self-perceptions of their ability to perform well in courses. The four items on the student survey (S2MTESTS, S2MTEXTBOOK, S2MSKILLS, and S2MASSEXCL) asked students to rate how much they agree or disagree with statements about current or upcoming math courses. Item wording was as follows:

1. "You are confident that you can do an excellent job on tests in this course"
2. "You are certain that you can understand the most difficult material presented in the textbook used in this course"
3. "You are certain you can master the skills being taught in this course"

4. "You are confident that you can do an excellent job on assignments in this course"

All four items contained a four-point Likert Scale from "strongly agree" to "strongly disagree". The Cronbach's alpha for the Mathematics Efficacy Scale (X2MTHEFF) was high at 0.89. If a student indicated taking more than one course, the questions were only asked and referred to the self-reported course that appeared first on the survey. Courses are listed in order from most advanced to remedial math.

Interest

The Mathematics Interest Scale (X2MTHINT) represents students' overall interests in courses. Item wording for the four questions related to mathematics (S2MWASTE, S2MBORING, S2MENJOYS, and S2MENJOYING) are as follows:

1. "You think this class is a waste of your time"
2. "You think this class is boring"
3. "You really enjoy math"
4. "You are enjoying this class very much"

Three of the four questions were responded to on a four-point Likert Scale from "strongly agree" to "strongly disagree". Number four was a 'yes' or 'no' question (dichotomous variable). The Cronbach's alpha was low but adequate for research purposes at 0.69 for the Interest Scale.

Identity

The Mathematics Identity Scale (X2MTHINT) represents the extent to which participants distinctly viewed themself as mathematically inclined. There are two items

in this scale (SMPERSON1 and SMPERSON2); the Cronbach's alpha was high at 0.88. The questions were as follows:

1. "You see yourself as a math person"
2. "Others see you as a math person"

Similar to the self-efficacy and interest scales, participants responded on a four-point Likert Scale from "strongly agree" to "strongly disagree".

Parental Involvement

There are many questions in the parent survey; however, no Parental Involvement Scale existed in the HSLS:09/12 database. For this reason, I conducted an exploratory factor analysis using SPSS 22 on a set of 11 items from the Parent Survey. Nine items were related to how often a parent engages (Parent Engagement) with the student on different academic issues, and 2 were related to a parent's level of confidence in helping (Confidence Helping) the student with math or science homework.

1. How often they discussed selecting courses or programs at school
2. How often they discussed preparing for college entrance exams
3. How often they discussed applying to college/other schools after high school
4. How often they discussed careers he/she might be interested in
5. How often they discussed job that he/she might want to take after high school
6. How often they discussed community/national/world events
7. How often they discussed things that were troubling him/her

8. How often they contacted teen's school since start of 2011-2012 school year
9. How often they helped teenager with homework
10. Level of confidence in helping with math homework when last enrolled
11. Level of confidence in helping with science homework when last enrolled

The eleven items from the Parent survey were subjected to principal components analysis (PCA). Prior to performing PCA, the suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of many coefficients of .3 and above. The Kaiser-Meyer-Olkin value was .84, exceeding the recommended value of .6 (Kaiser, 1970; 1974), and Bartlett's Test of Sphericity (Bartlett, 1954) reached statistical significance, supporting the factorability of the correlation matrix.

The initial factor analysis, using principal components extraction and orthogonal factor rotation, produced three factors with eigenvalues greater than 1.0 (Table 2). The first factor was distinguished by strong factor loadings for 5 of the 9 Parent Engagement items (factor loadings greater than .70), moderate factor loadings for the remaining 4 items (between .397 - .690), and none for the Confidence Helping items. This factor explained 36.8% of the total variance in the items.

The second factor had strong factor loadings for the two items on Confidence Helping and none of the other items, and explained an additional 14.2% of the variance. The third factor produced overlapping items with 3 of the 9 Parent Engagement factors loadings of greater than .30. This factor explained 9.2% of the variance. An inspection of the screeplot revealed a clear break after the second component (Figure 3). Using

Catell's (1966) scree test, it was decided to retain two components for further investigation.

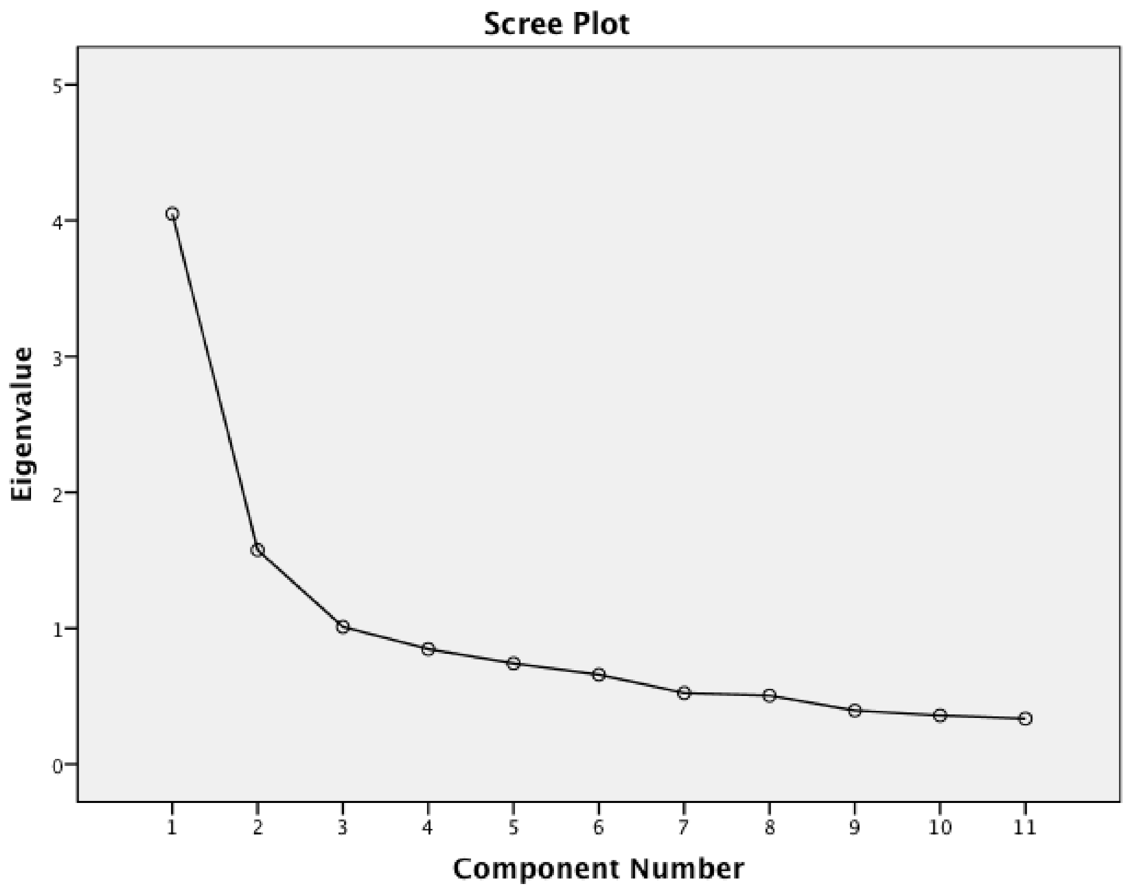

Figure 3: Screeplot used for Catell's (1966) scree test to determine how many components to retain for further analysis.

The two-component solution explained a total of 51.1% of the variance, with Parent Engagement factors (Component 1) contributing 36.8% and Confidence Helping factors (Component 2) contributing 14.3%. To aid in the interpretation of these two components, oblique rotation was performed. The rotated solution revealed the presence of components showing a number of strong loadings and all variables loading on one component. However, this subsequent factor analysis produced strong factor loadings for

4, instead of 5, PE items (Table 3). The interpretation of the two components was consistent with previous research of Jeynes (2003; 2005; 2007) with parental involvement items related to parent attempts to engage with students loading strongly on Component 1 and items related to parents' confidence in helping loading strongly on Component 2. There was a weak correlation between the two factors (-.086). The results of this analysis support the use of four items from Component 1 in a Parental Involvement Scale.

Next, a reliability analysis was performed to examine the internal consistency of the PE factor produced by the second exploratory factor analysis. This reliability analysis revealed that the four extracted Engagement items formed a reliable scale (Cronbach's alpha = .82) and the alpha would not improve with the removal of any of the items. All four items had item-total correlations greater than .60. The final four items selected for the Parental Involvement Scale (PInv) were as follows:

1. "How often discussed selecting courses or programs at school"
2. "How often discussed preparing for college entrance exams"
3. "How often discussed applying to college/other schools after high school"
4. "How often discussed careers he/she might be interested in"

Socio-economic Status Composite

The socio-economic status composite variable (X2SES) in the HSLS:09/12 is derived from parental education level, parental occupation, and family income. More than 16 million children under the age of 18 in the United States live in poor families, as defined by homes with incomes below the federal poverty level (FPL; Addy, Engelhardt, & Skinner, 2013). Researchers have identified SES as a significant factor associated with

students' academic performance, across racial groups (e.g., Linnehan, Weer, & Stonely, 2011; Sung, Padilla, & Silva, 2006). According to Frederickson and Petrides (2008), students from high SES backgrounds outperformed their peers from lower SES backgrounds. Additionally, the NCES (2011) presented statistics that indicated a disproportionate distribution of Black and Hispanic students within the lowest percentile of mathematics performance. Compared to 72% of the European Americans, 5% of Black/African Americans, 11% of Latin Americans, and 10% of Asian American eighth-graders scored above the 75th percentile in 2011. Due to prior research related to the impact of SES on achievement, this variable was controlled for in this dissertation.

Mathematics Theta Score

Each of the participants in the HSLS:09/12 study completed an online mathematics test of algebraic reasoning. The mathematics theta score (X2TXMTH) was used in this dissertation as a measure of STEM achievement in algebra. The theta score variable is an ability estimate. The purpose of the HSLS:09/12 mathematics assessment was to provide algebra achievement measures at two points in time: 1) during the fall semester of the ninth grade (N = 20,956); and, 2) during the spring semester of the 11^{th} grade (N = 18,507). The American Institutes of Research developed the instrument used to measure the algebra proficiency of the participants. A Mathematics Advisory Panel (MAP) of three professors of mathematics reviewed the development of the instrument, validating the framework and approving each item (Ingels et al., 2011). The MAP consisted of a retired secondary mathematics teacher, and a mathematics education consultant. The test and item details address the following six algebraic content domains: a) the language of algebra; b) proportional relationships and change; c) linear equations,

inequalities, and functions; d) nonlinear equations, inequalities, and functions; e) systems of equations; and f) sequences and recursive relationships. Additionally, there are four algebraic processes addressed - demonstrating algebraic skills, using representations of algebraic ideas, performing algebraic reasoning, and solving algebraic problems. Item analyses (including differential item functioning statistics) were conducted to collect a pool of optimally performing items and to detect potential racial/ethnic and gender biases.

Base year. The 72 items used to compile the base year test were derived from an initial set of 264 items that were field tested with 2,751 9^{th}-12^{th} graders (Ingels et al., 2010). The assessment was timed at 40 minutes. The HSLS:09/12 base year variable X1TXMSCR represents an IRT-based estimate of the score for each participant on the full set of 72 items. The assessments were completed and monitored at the participants' schools sites by project senior administrators (SA) and their assistants. The assessments were administered during school hours on school computers, project laptops, or a combination of the two depending on school capacity. The assessments were completed by the participants, on one of three different test dates, during the fall term of their ninth-grade school year (September 2009, October 2009, or January 2010).

First follow-up. A second algebra assessment addressing the previously listed six algebraic content domains and four algebraic processes was administered during the spring semester of the study cohort's junior year. The follow-up theta score variable (X2TXMTH) was used to compare participant scores over both waves as the common items between waves allowed for equating the IRT scores across waves. The follow-up assessment contained a 69-item pool, including 23 common items across the two waves.

The assessment was administered with a 40 minute, two-stage, 40-item format similar to wave one. The IRT-estimated reliability of this follow up assessment was 0.92 after sample weights were applied (Ingels et al., 2014). The in-school assessments were administered similar to the base year collection. Any out-of-school assessments were completed via the Internet, a computer-assisted telephone interview, or a computer-assisted personal interview.

Multiple Regression

Regression analysis allows for an examination of how well predictor variables predict an outcome variable (Muijs, 2011). Multiple regression (MR) is similar to simple linear regression; however, two or more predictor variables are used to predict the criterion (Pallant, 2013). Furthermore, MR is based on correlation with a refined examination of the interrelationship among a set of variables. For example, an exploration occurs in this dissertation to determine how well sets of scales related to motivation predict performance on a study-administered test. MR provides the big picture of the model considering all scales and the influence of each variable within the model. MR allows for testing whether the inclusion of additional variables (e.g., parental involvement) contributes to the predictive ability of the model (Pallant, 2013). Predictive ability refers to the predictive power by which each independent variable (IV) is evaluated.

In summary, the purpose of MR is to examine the relationship between IVs and a DV. If a relationship exists, using the information in the IVs improves accuracy in predicting values for the DV (Howitt & Cramer, 2014). Calculating separate correlations or t-tests between two variables is not appropriate for this research, as it does not account

for relationships among other variables. For example, certain variables that might predict achievement (e.g., self-efficacy, interest, and prior grades) for female high school students may also be related to one another. If bivariate measures were calculated between achievement and each of these variables, the effect found for any variable on achievement would not have taken into account the fact that a part of the relationship was influenced by another variable.

Hierarchical Multiple Regression

The three main types of MR analyses include the following: standard or simultaneous, hierarchical or sequential, and stepwise. Standard regression is utilized to examine relationships between a set of IVs and a DV. Stepwise regression is used to determine a subset of IVs with the strongest relationship to a DV. Hierarchical multiple regression (HMR) extends one step further than both standard and stepwise regression, and has been noted as a robust method for partitioning variance (Cohen & Cohen, 1983). HMR is utilized to evaluate relationships among a set of IVs and a DV after controlling for the effects of some other IVs on the DV. Furthermore, HMR is commonly used as a tool for analyzing data when variance on a criterion variable is explained by correlated predictor variables (Pedhazer, 1997).

Simultaneous regression and stepwise regression are often used to explore and maximize prediction; alternatively, HMR is used to examine specific theory-based hypotheses (Aron & Aron, 1999; Cohen, 2001). A sound theoretical decision made by the researcher determines the order to use when entering predictor variables into the equation for analysis (Howitt & Cramer, 2014). R^2, the squared multiple correlation coefficient, estimates the DV variance associated with each predictor block. R^2 is

determined by dividing the sum of squares due to regression by the sum of squares about the mean. An effect size calculation, in the form of a percentage of criterion variance accounted for, is interpreted. For example, an R^2 coefficient of .4903 is explained as 49.03% of total criterion variance accounted for. Cohen (1988) provided the following guidelines for interpreting R^2 as an effect size: a) "small" is .01; b) "medium" is .09; and c) "large" is .25. The squared multiple correlation coefficient (ΔR^2) is an essential component in the HMR analyses, as it indicates the proportion of variance explained by a model. The change in R^2 is a way to evaluate the amount of predictive power added to the model when another variable is entered in a subsequent step.

In addition to the squared multiple correlation coefficient, the incremental *F* ratio test (F_{inc}) can be used to determine if a subsequent block of variables provides for statistically significant increases above the variance predicted by any variables previously entered into the equation. Then, the statistical output is interpreted based upon whether it meets a predetermined significance level (e.g., $p < .05$). The predictors in block 1 can be tested utilizing the conventional *F* ratio test.

HMR, as described above, was conducted using SPSS. In summary, the first stage of HMR includes inputting the IVs desirable of controlling into the regression equation (block 1). Next, the IVs to be examined after the controls are inputted (block 2). The remaining variance accounted for by the IV(s), in stage two, is then examined through effect size estimates. To follow, a statistical test of the change in R^2 is used to evaluate the significance of the variables entered.

Assumptions

Multiple regression makes numerous assumptions about the data and is known to be less forgiving when they are violated (Pallant, 2013). The following assumptions will be discussed in this section: a) sample size; b) multicollinearity; c) outliers; and, d) normality, linearity, homoscedasticity, and independence of residuals.

Sample size. Sample size is of key importance when attempting to generalize results to other samples. Researchers (e.g. Stevens, 1996; Tabachnick & Fidell, 2005) have recommended approximately 15 participants for each predictor for a reliable equation. A formula for calculating the sample size requirement is $N > 50+8m$, where m is equal to the number of independent variables. For example, if a researcher has four independent variables then 82 cases are needed. Additional cases are needed if the dependent variable is skewed.

Multicollinearity. Multicollinearity and singularity refer to the relationship amongst the independent variables. Multicollinearity occurs when there is a high correlation (r=0.9 and above) among the independent variables. The existence of multicollinearity should be determined before running HMR to contribute to a suitable regression model. SPSS may also be used to detect multicollinearity. A coefficient table will provide the Tolerance and Variance Inflation Factor; a Tolerance value less than .10 and a Variance Inflation Factor above 10 indicate possible multicollinearity.

Outliers. Outliers are the extreme scores that should be determined during the data cleaning process. Although this determination can be made before running any statistical analysis, procedures for identifying outliers are available in SPSS within the HMR process. If a very high or very low score is identified, it should be removed from

the dataset or replaced with a high score that is similar to the remaining scores. Viewing a standardized residual plot (generated in the HMR procedure) may help identify outliers (values above 3.3, or less that -3.3) on dependent variables (Tabachnick & Fidell, 2005).

Additional assumptions. Pallant (2013) defined residuals as the variance among the obtained and the predicted DV scores. Residual scatterplots are also useful in determining normality, linearity, and homoscedasticity. These assumptions refer to characteristics of the score distribution, as well as the relationship between the variables.

Normality. Normality refers to the distribution of scores; the residuals should be normally distributed around the predicted DV scores. In addition to scatterplots and histograms, there are statistical methods to use when testing for normality, such as a hypothesis test for normality. Generally, a variable is considered normal if its skewness and kurtosis values are between -1.0 and 1.0. Skewness and kurtosis are statistical measures that explain the distribution of the data around the mean.

Linearity. Linearity is also visible in graphs and describes the relationship between a variable and a constant, where they are related by their closeness to a straight-line. The assumption for linearity is that the residuals should be linear (or have a straight-line) to the DV scores.

Homoscedasticity. Homoscedasticity refers to the variability in scores for variables; the variance of the residuals around the predicted DV scores should be similar at all values for the other predicted scores. A scatterplot may be used to determine homoscedasticity.

Strengths and Limitations of HMR

Unlike standard or stepwise regression, HMR allows for a determination to be made about the relationship between variables. In other words, an additional value for R^2 change in variance is provided for subsequent blocks. The *F* test for subsequent blocks allows the researcher to determine if the additional variance accounted for by the variable is significant. There are potential limitations of using HMR that may result from the following errors: a) lack of a theoretical basis for using HMR; b) abuse of causal priority or relevance for the analysis; c) inappropriate interpretation of results; and d) the exploratory use of HMR. The above errors contribute to limitations such as the failure to assess potential issues of multicollinearity and a focus on the overall model and not discrepancies determined when comparing results. Both these limitations may negatively impact the results, as well as the interpretation of the findings (Cohen & Cohen, 1983). Another limitation related to the misuse of this analysis is specifically neglecting to provide a theoretical basis for using HMR. It is important to note that the researcher making theory-based decisions on the predetermined order of variable entry may minimize the latter limitation.

Rationale

Although this researcher has not found studies that use HMR to examine data in the HSLS:09/12, Engberg and Gilbert (2014) used HSLS:09 data and employed MR to identify factors related to the college-going culture of a high school and to categorize schools based upon the structure of their counseling opportunities, respectively. Their use of MR was based upon the single-level of analysis. However, Hwang (2002) asserted that MR is not appropriate to use with large datasets given the non-independence of the

data. The HSLS:09/12 dataset contains both multilevel (e.g., students clustered within schools) and longitudinal data; therefore, HMR is appropriate to use in this dissertation. Despite the limitations, the researcher's careful attention to the noted errors may result in a more robust approach to analyzing the HSLS:09/12 data. Hierarchical analysis of the variables in the HSLS:09/12 may add to the researcher's understanding of motivation and achievement in female high school students, as this method requires thoughtful consideration in determining the order of entry of IVs. Additionally, tests of the validity of the hypotheses that also determine the order may strengthen any arguments or recommendations made for future policy or practice.

Data Cleaning and Editing

The questionnaire data for the HSLS:09/12 were stored in a SQL database. The web survey was administered using a Computer-Assisted Telephone Interviewing (CATI) system and stored using the same SQL database. An abbreviated hard-copy instrument was used for the collection of parent data. The purpose for the design of the parent questionnaire was to simplify to the process for pulling and entering specific questions into the parent database. The editing program developed for the HSLS:09/12 was designed to extract inconsistent items across logical patterns. Additionally, programs were developed to review the consistencies across the multiple sources of data, and to further identify discrepancies that may have required resolution. For example, if a student's sex was collected from a student and/or parent questionnaire that did not match the data obtained from the school, the student's first name may be reviewed to determine and store the correct data value in the SQL database (NCES, 2011).

Additional data cleaning was required before proceeding with the HMR (discussed in the subsequent section). Data for all cases of female students were extracted from the HSLS:09/12 database using SPSS 22. A dataset of 11,493 female students were retained for the analysis in this dissertation (Table 4). The demographics provided in Table 4 are nationally representative of female students in the United States population. Demographics for the cases (N = 3,938) used in this dissertation are listed in Table 5. The discrete differences in percentages between the nationally representative sample and the sample presented in Table 5 indicated that the selected subset for analysis in this dissertation also represented the United States population at the time the data were collected. A chi-square goodness of fit test indicated there were no significant differences in the population sample as compared to the study sample, with an asymptotic significance of .136 (Figure 4).

X2 Student's race/ethnicity-composite	Observed N	Expected N	Residual
Amer. Indian/Alaska Native, non-Hispanic	18	27.5	-9.5
Asian, non-Hispanic	302	318.7	-16.7
Black/African-American, non-Hispanic	436	401.3	34.7
Hispanic, no race specified	26	35.4	-9.4
Hispanic, race specified	598	621.6	-23.6
More than one race, non-Hispanic	334	338.3	-4.3
Native Hawaiian/Pacific Islander, non-Hispanic	21	19.7	1.3
White, non-Hispanic	2203	2175.5	27.5
Total	3938		

Figure 4: Chi-square analysis of population sample and study sample

Analyses

After cleaning the data, statistical analyses (HMR) were performed on the final set of 3,938 female participants. Hierarchical Multiple Regression was used in this dissertation to examine the relationship between STEM achievement and motivation for female high school students. Based upon prior research related to the known effects of SES on achievement, socioeconomic status was entered into Block one. The motivational measures and parental involvement were entered into Block 2. The results after controlling for the effects of SES and the addition of the variables “self-efficacy”, “interest”, and “parental involvement” are outlined below in the findings section. Table 6 contains a list of the variables and analyses used in this dissertation.

Potential Ethical Issues

Although this dissertation utilized a publicly available database, there are ethical issues to consider. For example, the researcher cannot and will not use student identification numbers, locales, or any other case descriptor to attempt to locate participants and/or in the HSLS:09/12 database. The researcher acknowledges the Institute of Education Sciences' (IES) and the National Center for Education Statistics (NCES) as the data source and agreed to the privacy principles set forth upon download of the HSLS:09/12 data.

CHAPTER 4: Results

Hierarchical multiple regression was used to assess the ability of measures (Students' Mathematics Self-Efficacy Scale, Students' Interest in Math Scale, Students' Identity in Math Scale, and Parental Involvement Scale) to predict achievement in STEM for female high school students, after controlling for the influence of socio-economic status. Preliminary analyses were first conducted to determine any violations of the assumptions. Findings for the HMR will be discussed in this section, after the following assumptions have been addressed: a) sample size; b) multicollinearity; c) outliers; and, d) normality, linearity, homoscedasticity, and independence of residuals.

Sample Size

As previously noted in Chapter 3, sample size is essential when attempting to generalize results to other samples. Researchers (e.g., Stevens, 1996; Tabachnick & Fidell, 2005) have recommended approximately 15 participants for each predictor for a reliable equation. A formula for calculating the sample size requirement is $N > 50+8m$, where m is equal to the number of independent variables. In this dissertation, there were four independent variables; therefore, 82 cases were required to proceed with the HMR. After removing cases with missing data, the sample size is 3,938 ($N > 82$) and there was no violation of this assumption. Additional cases were not needed, as the dependent variable was not skewed (Figure 5).

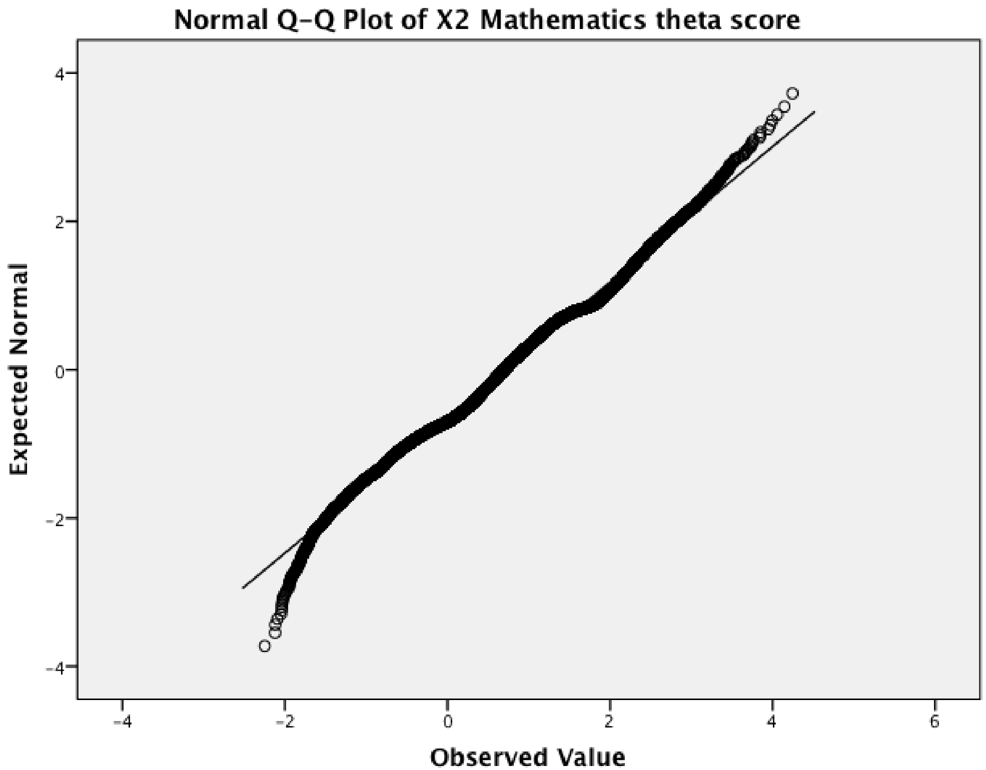

Figure 5: Output of a Normal Q-Q Plot with normally distributed dependent data (Mathematics Theta Score)

An a priori power analysis indicated that only 1,160 participants would be necessary to have 80% power for detecting a medium sized effect when employing the traditional .05 criterion of statistical significance (95% Confidence Interval). A post-hoc power analysis was also conducted to confirm the inclusion of sufficient participants to detect with inferential statistics and the actual medium effect size found (0.18) attributable to the addition of Model 3. Observed power for the addition of Model 3 was 1.0 (Power > .80). In summary, a strong chance existed for producing a statistically significant result assuming the population effect was equal to the study sample.

Multicollinearity

Multicollinearity refers to the relationships among the independent variables. As noted in chapter 3, multicollinearity occurs when there is a high correlation (r=0.9 and

above) among the independent variables. SPSS 22 was used to determine the correlations among the variables used in this dissertation (Table 7). A coefficient table (Table 8) was then used to confirm the Tolerance and Variance Inflation Factor. The Tolerance value was more than .10 and the Variance Inflation Factor was less than 10; therefore, this assumption has not been violated and the variables contribute to a suitable regression model (Pallant, 2013).

Outliers

Outliers are the extreme scores that should be determined during the data cleaning process. SPSS 22 was used to identify ten outliers (Figure 6). Before proceeding with HMR, the very high and very low scores (values above 3.3, or less that -3.3) were removed from the dataset to avoid violating this assumption of outliers (Table 9).

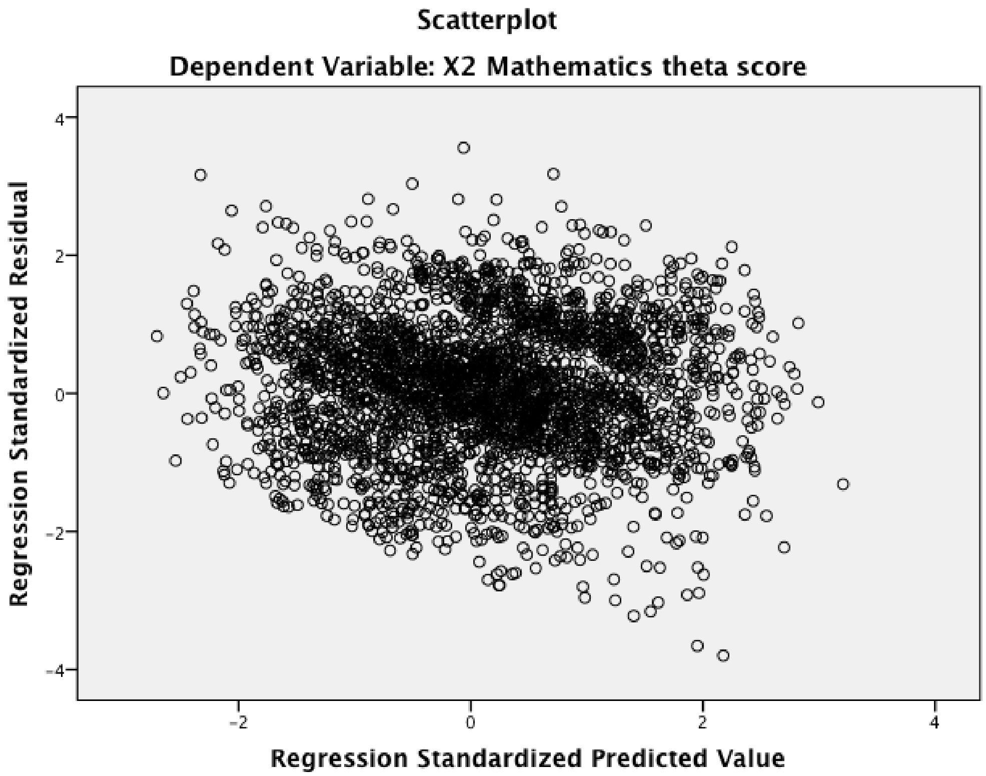

Figure 6: A standardized residual plot, generated in the Hierarchical Multiple Regression procedure. This scatterplot contains outliers.

Additional Assumptions

There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.932. The Durbin-Watson statistic can range from 0 to 4, but a value of approximately 2 indicates that there is no correlation between residuals. Because the Durbin-Watson value is very close to 2, it can be accepted that there is independence of errors (Laerd Statistics, 2013). Residual scatterplots are also useful in determining normality, linearity, and homoscedasticity.

Normality refers to the distribution of scores; the residuals should be normally distributed around the predicted DV scores. The standardized residuals appear to be approximately normally distributed based upon the histogram (Figure 7) and P-P Plot

generated in SPSS. A P-P Plot is a probability-probability used to determine if a given set of data follow a specified distribution. For this research, it was approximately linear.

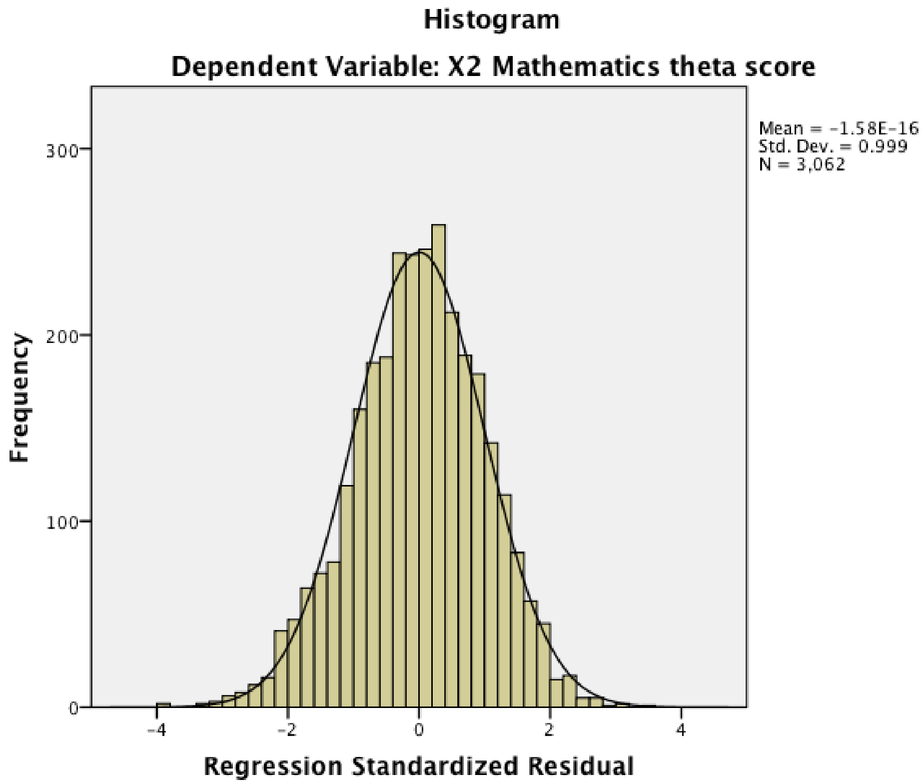

Figure 7: Histogram of normally distributed standardized residuals.

Skewness is a measure of symmetry, or the lack of symmetry. A distribution is symmetric if it looks the same to the left and right of the center point on a graph. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution (Pallant, 2013). Skewness and kurtosis values within the range of +/-1, or with a Standard Error (*SE*) range of +/- 2, are generally considered normal. According to Pallant (2013), positive skewness values indicate that scores may be clustered to the left at lower values, and negative skewness values indicate a clustering to the right (at the high end). A positive kurtosis value indicates a peaked distribution, and values below 0 indicate a rather flat distribution (or too many extreme cases).

The skewness value for the Mathematics Theta Score was -.007 (S*E* = .040) and the kurtosis value was -.345 (*SE* = .079). The skewness value for the Mathematics Self-Efficacy Scale was -.297 (*SE* = .040) and the kurtosis value was -.122 (*SE* = .081). For the Math Interest Scale, the skewness value was -.037 (*SE* = .044) and the kurtosis value was -.676 (*SE* = .087). For the Math Identity Scale, the skewness value was .054 (*SE* = .040) and the kurtosis value was -.899 (*SE* = .080). The skewness value for the Parental Involvement Scale was .054 (*SE* = .039) and the kurtosis value was -.130 (*SE* = .078). The Socio-Economic Status Composite had a skewness value of .165 (*SE* = .039) and a kurtosis value of -.750 (*SE* = .078). Due to the reasonably large sample size (200 or more cases), skewness will not 'make a substantive difference in the analysis' and the risk of underestimating the variance based upon kurtosis is reduced (Tabachnick & Fidell, 2013, p.80). Additional tests were not used to evaluate skewness and kurtosis values as they are considered to be too sensitive with large samples (Pallant, 2013); however, an inspection of the histograms confirmed the normality of the distribution of scores.

The partial regression plots between each independent variable and the dependent variable were generated. If the variables are connected along a straight line, the relationship is likely to be linear. Partial Regression Plots with non-linear or curvilinear relationships should raise concerns about meeting the assumption of linearity (HyperStat, 2013; Laerd Statistics, 2013; Pallant, 2013). The partial regression plots between each independent variable and the dependent variable are not curvilinear, and they display a range from a somewhat linear relationship to a linear relationship (Figures 8-12).

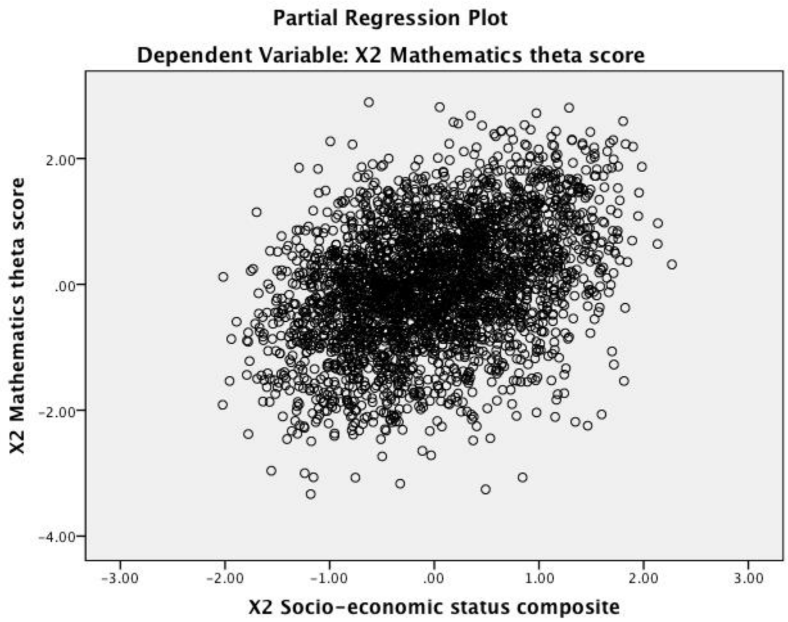

Figure 8: A partial regression plot with a linear relationship between Mathematics Theta Score and the SES composite.

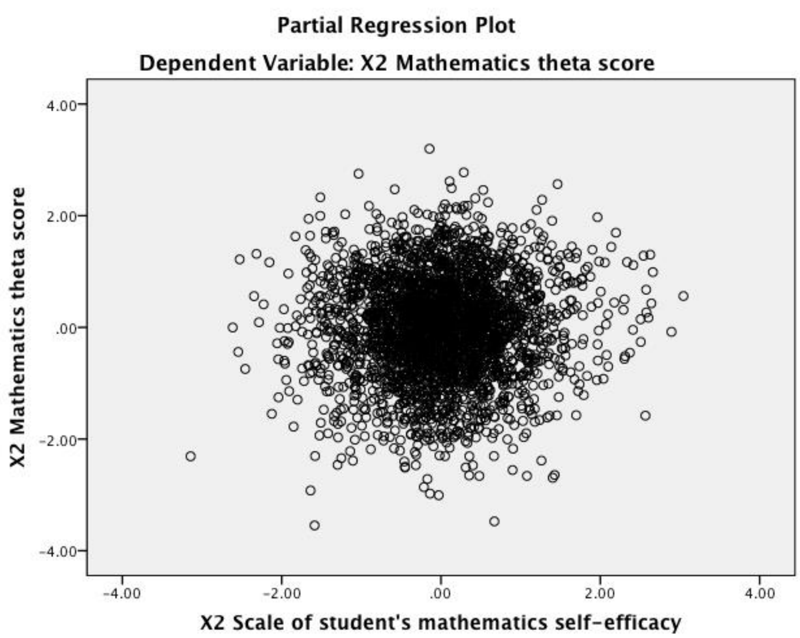

Figure 9: A partial regression plot with a weak linear relationship between Mathematics Theta Score and the Mathematics Self-Efficacy.

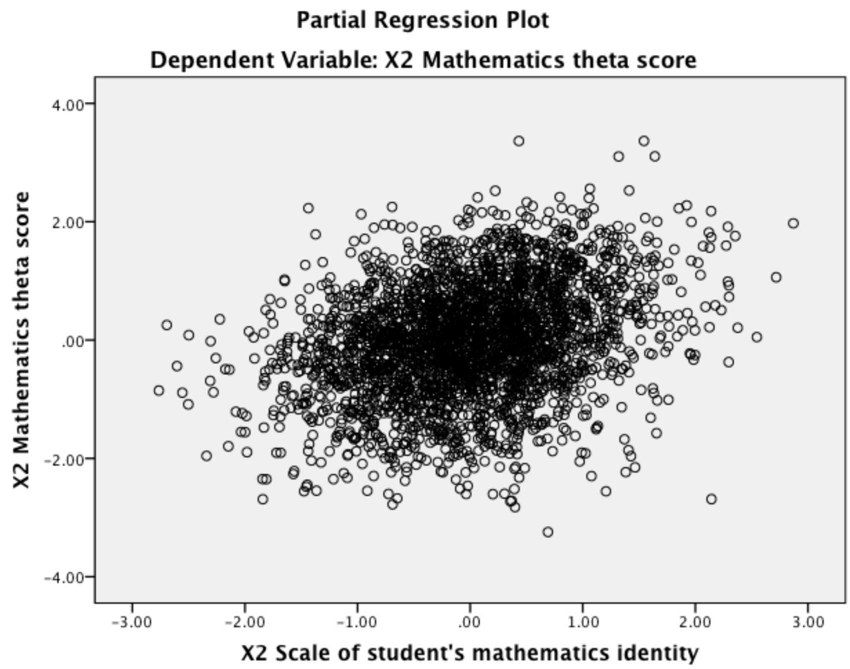

Figure 10: A partial regression plot with a linear relationship between Mathematics Theta Score and mathematics identity.

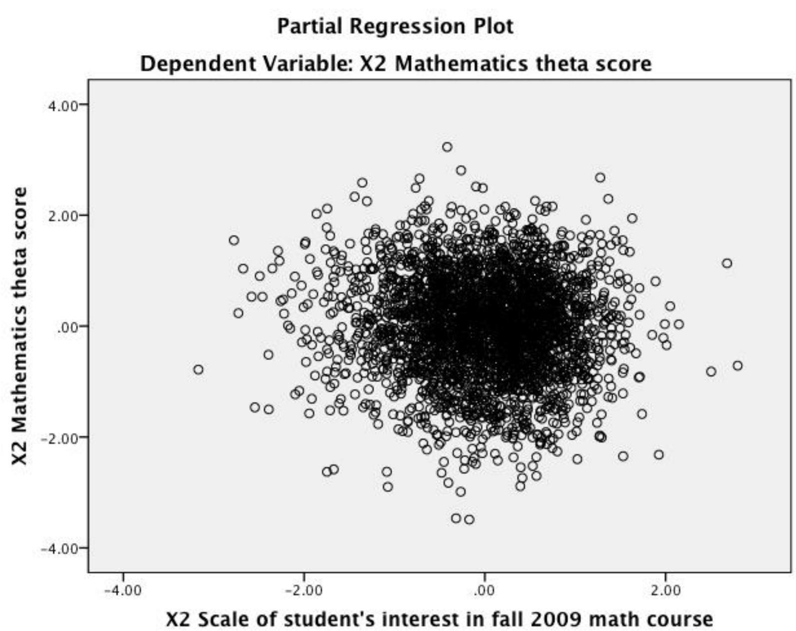

Figure 11: A partial regression plot with a weak linear relationship between Mathematics Theta Score and the scale of student's interest in math.

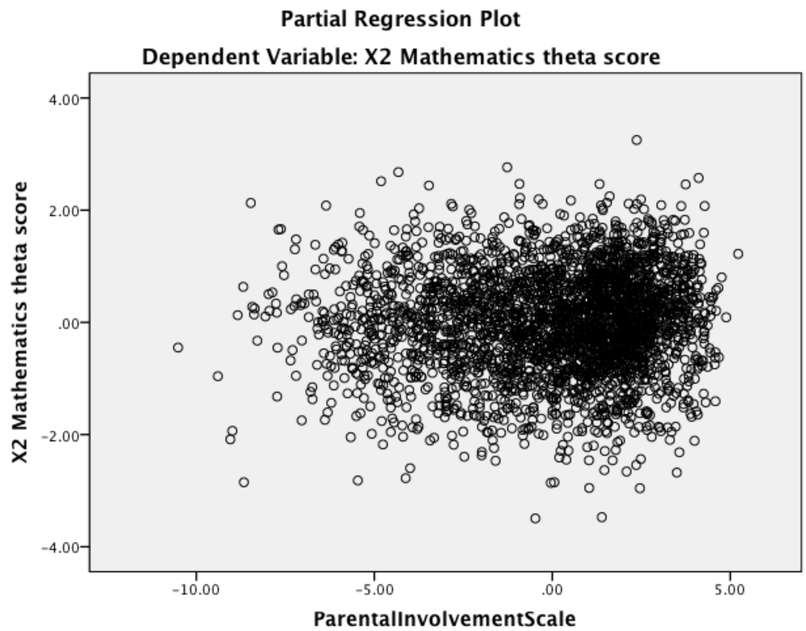

Figure 12: A partial regression plot with a somewhat linear relationship between Mathematics Theta Score and the Parental Involvement Scale.

Linearity is also visible in graphs and describes the relationship between a variable and a constant, where they are related by their closeness to a straight-line. Due to the fact that the Partial Regression Plots were not curvilinear, a transformation of variables was not required and the assumptions for normality and linearity were met (Laerd, 2014).

Results

Research Question 1: How well do motivational factors (e.g., self-efficacy, interest, or identity) and parental involvement predict STEM achievement in algebra for female high school students?

As mentioned in Chapters 2 and 3, researchers have found SES to be a confounding variable when examining factors related to achievement. Therefore, SES (a demographic variable) was entered at Step 1 as a control variable. Although SES is the control variable, the HMR model allowed for a determination of the unique contribution it makes in the model, explaining 17% of the variance in math achievement. Since the

items in the motivation scales were related to students' self-perceptions, the Math Self-Efficacy Scale, Math Interest Scale, and Math Identity Scale were entered at Step 2, explaining an additional 12% of the variance (Table 10). The Parental Involvement Scale contained questions related specifically to parents; therefore, it was entered at Step 3 and explained less than 1% of the variance in math achievement. After entry of all measures at Step 3, the total variance explained by the final model as a whole was 29.4%, F (5, 3,133) = 261.03, $p < .001$ (Table 11). In the final model, the predictive power of self-efficacy, interest, and identity combined was greater (an R^2 change of .120) than parental involvement (R^2 change of .007).

Hypothesis 1: Mathematics self-efficacy is a stronger predictor of STEM achievement than mathematics interest for female high school students

The results support this hypothesis. After entry of SES at Step 1, the three scales related to mathematics were entered at Step 2 explaining an additional 12% of the variance in achievement for female high school students. The total variance explained at Step 2 was 29%, R squared change = .120, F change (4, 3,134) = 314.73, $p < .001$). In Model 2, neither the Scale of Mathematics Self-efficacy (SMS) nor the Scale of Mathematics Interest (SMI) were statistically significant predictors of STEM achievement. However, the *beta* value for the Scale of Mathematics Self-Efficacy was slightly higher (*beta* = .061, p = .002) than the Interest Scale (*beta* = -.050, p = .013). Therefore, mathematics self-efficacy was a stronger predictor of STEM achievement than mathematics interest for female high school students, although the differences were small.

Hypothesis 2 - Mathematics self-efficacy is a stronger predictor of STEM achievement than mathematics identity for female high school students

The results do not support this hypothesis. In Model 2, the Scale of Mathematics Self-Efficacy (SMS) was not a significant predictor; however, the Scale of Mathematics Identity (SMID) was a statistically significant predictor of STEM achievement. The *beta* value for the SMID was higher (*beta* = .338, $p < .001$) than the *beta* value for the SMS (*beta* = .062, $p = .002$). Therefore, mathematics self-efficacy was not a stronger predictor of STEM achievement than mathematics identity for female high school students.

Hypothesis 3 - Mathematics identity is a stronger predictor of STEM achievement than parental involvement for female high school students

The results support this hypothesis. In Model 2, SMID was a statistically significant predictor of STEM achievement with *beta* value of .338 ($p < .001$). After entry of the Parental Involvement Scale (PInv) at Step 3, mathematics identity remained a significant predictor of achievement for female high school students with the *beta* value .336 ($p < .001$). The *beta* value for the SMID was higher than the PInv (*beta* = .093, $p < .001$). Therefore, mathematics identity was a stronger predictor of STEM achievement than parental involvement for female high school students.

Research Question 2: Do motivational factors (e.g., self-efficacy, interest, or identity) predict achievement for female high school students, differently, when race is considered?

As mentioned previously, SES (a demographic variable) was entered at Step 1 as a control variable. Although SES is the control variable, the HMR model allowed for a determination of the unique contribution it makes in the model. Similar to the previous

HMR analysis, the motivation scales for self-efficacy, interest, and identity were entered at Step 2, and the Parental Involvement Scale was entered at Step 3. Results by race are discussed in the subsequent section on hypothesis 4; however, it is important to note that the only scale that was statistically significant for Black/African American females was Math Identity with a *beta* value of .220 ($p = .001$). For European American females, the Math Identity Scale was the only statistically significant finding with a *beta* value of .363 ($p < .001$). The Math Identity Scale also had the highest *beta* value of .290 ($p < .001$) for Hispanic females. Similarly, the Math Identity Scale was the most significant predictor of achievement in the model for Asian American females with a *beta* value of .317 ($p < .001$). These findings, by race, support the initial findings for all female high school students. Mathematics identity was the strongest predictor of achievement for female high school students in this study, regardless of race (Figure 13).

	Identity (*Beta* and *p* value)		Interest (*Beta* and *p* value)		Self-Efficacy (*Beta* and *p* value)		Parental Involvement (*Beta* and *p* value)	
Asian American	.317	.000	.071	.262	.081	.203	.027	.646
Black/ African American	.220	.001	.016	.807	.041	.522	.129	.014
Hispanic/Latin American	.290	.000	.057	.302	.080	.148	.065	.149
European American	.363	.000	.079	.004	.076	.005	.160	.000

Figure 13: Beta and P-values for Predictors, by Race

Hypothesis 4 - Parental involvement is a stronger predictor of STEM achievement for black female high school students than for other races

Results for Black/African American females. As noted in the previous section, the Parental Involvement Scale was not a strong predictor of achievement for the overall population of female high school students (*beta* = .093, $p < .001$) in this study. A sample of Black/African-American females (N = 436) was extracted from the female high school sample for this analysis; the same variables and three models were used to conduct HMR. SES was entered at Step 1, explaining 11.1% of the variance in perceived achievement. After entry of the Students' Math Self-Efficacy Scale, Math Interest Scale, and Math Identity Scale at Step 2, an additional 6.2% of the variance was explained in the Model Summary (Table 12). The Parental Involvement Scale was then entered at Step 3, explaining an additional 1.5% of the variance in algebra achievement. After entry of all measures at Step 3, the total variance explained by the final model was 18.8%, F (5, 326) = 15.096, $p < .001$ (Table 13). In the final HMR model (Table 14), the Parental Involvement Scale had a *beta* value of .129 ($p = .014$).

Results for European American females. A sample of European American females (N = 2,203) was extracted from the initial female high school sample for this analysis; the same variables and three models used for the analysis with all female high school students and the Black/African-American females were used to conduct the HMR for this sample. SES was entered at Step 1, explaining 15.7% of the variance in perceived achievement. After entry of the Students' Math Self-Efficacy Scale, Math Interest Scale, and Math Identity Scale at Step 2, an additional 13.9% of the variance was explained in the Model Summary (Table 15). The Parental Involvement Scale was then

entered at Step 3, explaining an additional 2.2% of the variance in perceived achievement. After entry of all measures at Step 3, the total variance explained by the final model as a whole was 31.9%, F (5, 1,752) = 164.314, $p < .001$ (Table 16). In the final HMR model (Table 17), the Parental Involvement Scale had a *beta* value of .160 ($p < .001$).

Results for Hispanic/Latino American females. A sample of Hispanic/Latino American females (N = 598) was extracted from the initial female high school sample for this analysis; the same variables and three models were used for the analysis with all female high school students, European American females, and the Black/African-American females were used to conduct the HMR for this sample. SES was entered at Step 1, explaining 10.2% of the variance in perceived achievement. After entry of the Students' Math Self-Efficacy Scale, Math Interest Scale, and Math Identity Scale at Step 2, an additional 10.1% of the variance was explained in the Model Summary (Table 18). The Parental Involvement Scale was then entered at Step 3, explaining an additional .4% of the variance in algebra achievement. After entry of all measures at Step 3, the total variance explained by the final model as a whole was 20.6%, F (5, 456) = 23.665, $p < .001$ (Table 19). In the final HMR model (Table 20), the Parental Involvement Scale had a *beta* value of .065 ($p = .129$).

Results for Asian American females. A sample of Asian American females (N = 302) were extracted from the initial female high school sample for analysis; the same variables and three models used for the analysis with all females high school students was used to conduct the HMR for this sample. SES was entered at Step 1, explaining 17% of the variance in perceived achievement. After entry of the Students' Math Self-Efficacy

Scale, Math Interest Scale, and Math Identity Scale at Step 2, an additional 11.1% of the variance was explained in the Model Summary (Table 21). The Parental Involvement Scale was then entered at Step 3, explaining an additional .1% of the variance in algebra achievement. After entry of all measures at Step 3, the total variance explained by the final model as a whole was 28.1%, F (5, 268) = 20.945, $p < .001$ (Table 22). In the final HMR model (Table 23), the Parental Involvement Scale had a *beta* value of .027 and a *p*-value of .646.

The final results did not support the hypothesis that parental involvement was a stronger predictor of achievement for Black/African American female students than those of other races. Although parental involvement was a stronger predictor of achievement for Black females than Asian American and Latin American females, the *beta* value for this scale was higher for European American females than Black/African American females.

CHAPTER 5: Discussion

The purpose of this study was to evaluate motivational factors (self-efficacy, interest, and identity) and parental involvement as predictors of STEM achievement in algebra for female high school students. Previous researchers have interpreted even the most questionable results related to motivation, parental involvement, and achievement with rose-colored glasses. Without question it is important to address the limitations of any given research; however, plausible explanations beyond the admission of a failure to capture the complexity of the relationships among dependent and independent variables is paramount. The findings in this dissertation offer practical and policy implications regarding the factors related to STEM achievement for female high school students. My final thoughts regarding the findings in this dissertation will hopefully add to the current body of research related to the predictors of achievement for female high school students in STEM. This chapter is comprised of four major sections: a) a review of the results found for the research hypotheses outlined in Chapter 3; b) implications for policy and practice; c) the strengths and limitations of the current study; and d) future research directions.

Research Hypotheses

Hypothesis 1: Mathematics self-efficacy is a stronger predictor of STEM achievement than mathematics interest for female high school students

The results supported this hypothesis. Mathematics self-efficacy was found to be a stronger predictor of STEM achievement than mathematics interest for female high school students. Support for this hypothesis is consistent with previous research. Yet, it is important to mention the *beta* value (.060) and *p*-value ($p = .003$) which indicate there

is significance, but a small effect for mathematics self-efficacy as a predictor of STEM achievement. The results for this hypothesis may be related to the development of the Mathematics Self-Efficacy Scale in the HSLS:09/12 study, which will be discussed in the subsequent section on limitations.

Hypothesis 2: Mathematics self-efficacy is a stronger predictor of STEM achievement than mathematics identity for female high school students

Previously, researchers found that higher levels of self-efficacy predicted academic effort, persistence, learning, achievement, course enrollment, and career choice (Bandura, 1997; Pajares, 1996; Pintrich & Schunk, 2002; Schunk, 1995; Schunk & Pajares, 2002). Although mathematics self-efficacy was not found in the current study to be a stronger predictor of STEM achievement than mathematics identity for female high school students, it did not come as a surprise. According to prior research, female students may be more likely to acquiesce in instances when stereotype threat exists. Gender-based stereotypes have also been found to be a factor related to the achievement (or lack of achievement) in STEM for female students.

Hypothesis 3: Mathematics identity is a stronger predictor of STEM achievement than parental involvement for female high school students

In this study, mathematics identity was found to be a stronger predictor of STEM achievement than parental involvement for female high school students. This finding is consistent with prior research. Upon reflection of the role that gender has played in society, levels of identity may naturally be stronger predictors of achievement in content areas considered to be male-dominated. Researchers have noted the importance of parental involvement, but the literature lacks a succinct definition of this form of support

to students. Jeynes (2007) indicated that two components of parental involvement had a significant relationship to higher academic achievement: (a) parental involvement as an investment of time; and (b) parental involvement related to parenting style and expectations. Yet Armor (2006) contended that emotional support given at home and a child's nutrition are key components of parental involvement.

Hypothesis 4: Parental involvement is a stronger predictor of STEM achievement for Black/African American female high school students, than those of other races

The results did not support this hypothesis. Prior research by Jeynes (2005) indicated a higher correlation between parental involvement and academic achievement for Black/African Americans and Hispanics/Latin Americans. Jeynes' research and similar research on this same topic were the basis for this hypothesis. Furthermore, parental involvement was not a significant predictor of STEM achievement for female high school students across racial groups in the current study. Although this research found no empirical support for the parental involvement hypothesis as it relates to female high school students in general, this should not suggest that parent involvement research be abandoned. According to Desimone (1999), the effect of parent involvement on student achievement varies by race and social class. Additionally, it is likely that parents of different SES and racial backgrounds may not use similar parental involvement strategies. Research has also shown variations by SES, familial background, and parental strategies.

Implications for Policy and Practice

According to NCES (2011), the transition of youth into adulthood is of particular interest to federal policy-makers and program initiators. The transition to adulthood is a

time of physical and psychological change. Environments influence when, how, and why students choose future courses and/or career trajectories. In addition to parents and educators, policymakers seek to understand the impact or lack of educational guidance from schools, as well as in the home. Additionally, parents, educators, and policy-makers share the need to understand the effects guidance may have on the educational, career, and social outcomes for youth.

The significant underrepresentation of females in STEM fields persists; therefore, policy-makers, as well as educational planners and practitioners, should not allow the discussion on how to engage this population to become a moot point. As researchers and academic leaders continue to make efforts to identify the root causes for the underrepresentation of females in STEM fields, more attention should be given to the ways in which female high school students are motivated and supported on STEM quests. Much of the literature on STEM achievement for female students has focused on college courses or their discipline major selections. Specifically, researchers and policy-makers have sought to understand and/or address the reasons why female undergraduate students do not persist in STEM programs and careers.

The reasons why female students change majors/careers (within the sciences) seems to be more prominent in the STEM literature than the evaluation of why the female population may not consider STEM beyond the required courses in high school. Although the Obama Administration and policy initiators have invested funds into the development of school-based STEM programs, specifically for Black/African American and Hispanic/Latin American female students, their efforts do not directly address the motivational and parental support needs of females high school students. Based upon the

findings in this dissertation, higher levels of math identity for female high school students' indicate a greater likelihood they will achieve in STEM, at least as it pertains to mathematics-related courses (such as algebra). Perhaps greater funding should be directed towards mentorships and support groups for female high school students.

A practical component of a STEM mentorship program would address the need for female high school students to view self as a math or science person. Female high school students should be provided with mentors and a support team from the STEM field, who serve as a physical reflection of who they potentially aspire to become. Consistent with Bandura's social cognitive theory, specifically vicarious experience, an ability to see oneself as a person within a field of interest may begin with interacting with relatable others in your desired field.

Strengths and Limitations of the Current Study

In consideration of the national efforts to address the need for more females in STEM fields, the research in this dissertation was timely. Causal relationships cannot be determined through the research in this dissertation; however, the use of a nationally representative database positions the findings to be considered as more generalizable than would be similar findings with a smaller sample. The HSLS:09/12 focuses specifically on the transition of youth through the paths that lead students to pursue and persist in STEM courses and careers. Motivational factors and parental involvement are potentially key components of the school and life transitions that female high school students navigate.

As previously mentioned, the NCES (2011) encourages researchers to examine the data in the HSLS:09/12 and the relationships among tested achievement, choice,

access, and persistence. Additionally, the mathematics assessment in the HSLS was designed as an outcome measure and a predictor of a student's ability to advance in STEM courses and careers. In summary, the strengths of the research in this dissertation are related to the selected data and the predictive nature of the research. The data in this study were limited to students who completed the survey, questionnaire, and assessment during 9th and 11th grade. Current policy initiatives target middle-school students and the prior research related to the variables in this study address college-level students. Examining students beginning as early as middle school may provide more insight into the predictors of STEM career trajectory for female high school students. Additionally, the data do not address recent changes in the Next Generation Science Standards or Common Core State Standards, the changes in the students' self-efficacy or interest over time, or STEM teaching strategies.

Although this study was predictive in nature, the results revealed several essential findings regarding the efficacy of certain scales in the HSLS:09/12 that may call for examination. Most notably, the Mathematics Self-Efficacy Scale left room for question. According to previous research discussed in Chapter 2, higher levels of self-efficacy are generally related to higher levels of achievement. Furthermore, self-efficacy has been reported as a predictor of achievement for students. The findings in this study were not consistent with prior research; mathematics self-efficacy was not a strong predictor of achievement in STEM for female high school students. Therefore, a closer examination of the items in the HSLS Mathematics Self-Efficacy Scale may be appropriate.

There were four items in the Self-Efficacy scale for this study, as follows: 1) You are confident that you can do an excellent job on tests in this course; 2) You are certain

that you can understand the most difficult material presented in the textbook used in this course; 3) You are certain you can master the skills being taught in this course; and, 4) You are confident that you can do an excellent job on assignments in this course. The Cronbach's alpha for these four items was high at 0.89. The Patterns of Adaptive Learning Scales (PALS; The University of Michigan, 2000), also based on Bandura's social cognitive theory, defines Academic Efficacy as students' perceptions of their competence to do their class work. The items recommended in PALS for an efficacy scale are consistent with those recommended in Bandura's guide for creating self-efficacy scales, as follows: 1) I'm certain I can master the skills taught in class this year; 2) I'm certain I can figure out how to do the most difficult class work; 3) I can do almost all the work in class if I don't give up; 4) Even if the work is hard, I can learn it; and, 5) I can do even the hardest work in this class if I try. The Cronbach's alpha for these five items was moderate, and lower than the scale in this study, at 0.78.

At first glance, the items in the HSLS study appear to be clearer and more succinct in language, with a higher Cronbach's alpha (0.89 > 0.78). However, the language of the PALS recommended items are more consistent with the current shift to Common Core State Standards (CCSS). According to the Core Standards website, the key focus of CCSS is to prepare students for future education and careers through the establishment of clear and consistent guidelines for what students should know at each grade level. Decisions related to course content and materials are no longer solely in the hands of school districts. Instead, schools and teachers are now expected to make decisions on how to best serve the needs of their students while helping them to reach the CCSS. According to the CCSS, the teaching strategies used today should not be simply

driven by textbooks, and there has been a purposeful shift away from focusing on individual assignment completion and/or scores on chapter tests. Therefore, questions related to performance on course tests and assignments, or an ability to understand a textbook may not actually address the learning that takes place in the classes of students today.

Because the focus of CCSS is to address the need to better prepare students to enter a world with choices about college and careers, items similar to those on the PALS recommended list seem to be more related to proposed teaching practices. The PALS items not only address the present ability of a student, but also their perceptions of potential ability. How can a student confidently assess their certainty about their ability to understand material to be presented in a textbook (HSLS item number 2)? Under the new CCSS, students are expected to build skills in perseverance, work collaboratively, and use multiple modalities to showcase what they know or learn. Therefore, responding to a statement regarding their certainty in figuring out how to do the most difficult classwork (item number 2 of PALS) may be more in line with the teaching and learning in their present-day classroom. Perhaps the inclusion of words like "textbook", "assignment", and "test" impacted the responses of students to the items in the Mathematics Self-Efficacy Scale in the HSLS study.

Future Research Directions

The variance of the model including all female high school students indicated that only 29% of the variability in predicting STEM achievement was explained by motivational factors (mathematics self-efficacy, math interest, math identity), and parental involvement. The findings indicate that additional factors may need to be

considered to account for more variance. Other school level variables may be related to STEM achievement, such as science identity and self-efficacy, or the number of advanced level STEM courses. Additional factors to consider may be a teacher's instructional strategies or a student's level of participation in STEM related extra-curricular activities. Because the focus of the research in this dissertation was on the base-year (9th grade) and first-follow up (11th grade) data, third wave data on students may provide additional insight into the predictors of achievement for female high school students in STEM courses and/or careers.

Although the research in this dissertation used data from a national database, replicating this study at several diverse high school campuses may provide further evidence regarding the relationships among motivation (including parental involvement) and achievement for female high school students, by race. It will be important to consider the state of education today (or potential shifts), if this study is replicated. Although the phenomenon of self-efficacy as a factor of achievement was not supported in the findings of this study, future research should include a Self-Efficacy Scale more consistent with the Academic Efficacy Scale recommended by PALS. Additional scales should be taken under consideration when conducting future research.

Although it was not noted above, another limitation for this study was the exclusion of a Parental Involvement Scale in the HSLS database. According to previous research, parental involvement (in various forms) has been shown to have an influence on achievement. Surprisingly, the HSLS did not contain a scale for parental involvement in a study addressing the future of youth in transition. The HSLS did contain questions to parents about their involvement in their child's academics; however, the development of

the Parental Involvement Scale was necessary for the research in this dissertation. The findings positioned parental involvement as a weak predictor of achievement. This can be explained by the inclusion of SES as the variable in Block one (control variable), yet to more fully understand the relationship between parent involvement and student performance, researchers should focus on understanding or establishing a clearer definition of parent involvement.

Future Strategies to Support Identity Development

Although there were limitations for this study, the findings indicated that the mathematics identity of female high school students was a strong predictor of STEM achievement in algebra. Therefore, schools and teachers should seek new ways to foster the mathematics identity of female students. Through local districts, schools can access available funds to support the professional development of teachers, specifically related to learning how to support female students in the development of a positive mathematics identity. Teacher efforts should be visible beyond textbook lessons. Building innovation stations, such as MakerSpaces and BreakerSpaces, on school sites may provide enriching hands-on learning opportunities for female students.

MakerSpaces and BreakerSpaces are rooms used by students and/or teachers for STEM discovery and inventions. Teachers either bring in, or collect donations of, various items with the intention to either create a project from scratch (MakerSpaces) or to break apart and explore current technology (BreakerSpaces). The items in a MakerSpace may include recycled cans, wires, cardboard, tires, or any other resource to use for tinkering, playing, and creating. Old electronics, toys, and appliances are commonly found in BreakerSpaces. In both settings, students are provided with a space

to use their mathematical reasoning skills, scientific knowledge, and technology tools to deconstruct and construct STEM-related projects. A common location for these spaces is school libraries, but every teacher should consider creating an innovation station in their classroom. Maintaining a classroom innovation station addresses the issue of equitable access, while increasing the amount of time students spend connecting with STEM content. More time spent engaging with STEM-related concepts may increase the likelihood that a student will see herself as a math person.

STEM opportunities are also available to students out of school through afterschool programs and/or community partnerships. Funding for these programs has been available through the efforts of the Obama Administration, various higher education institutions, and/or local organizations. An increase in demand for more STEM programs often results in the rapid development of programs, yet quantity should not supersede quality. Questions about the outcomes of these programs, and whether the effective inclusion of identity development exists should be raised. Furthermore, policy-makers should shift the focus of current funding away from quick fix STEM programs to long-lasting STEM mentorship programs that connect students to relatable models of successful STEM professional who they may identify as similar to self.

There may be potential benefits to introducing STEM mentorship programs in elementary and middle school, such as an early development of a positive mathematics identity for female students. In the process of introducing mentorship programs and/or teaching strategies that support math identity development, every attempt should be made to hold female students to the same academic standards as their male counterparts and their female counterparts from other races. Continual encouragement and constant

exposure to math and science-related work should also be accessible to these young girls beyond in-school and after-school programs.

Summary

This study was conducted in response to the increasing concerns about the underrepresentation of females in STEM courses and careers. Understanding the factors related to the confidence, motivation, support, and persistence of females in science and mathematics is essential for the development of STEM fields. Based on the findings in this study, mathematics identity is an important construct that needs to be considered when developing future STEM courses and programs for female high school students. Finally, this study challenges the traditional notion that racial differences are a prominent factor in predicting achievement for female students. Although motivational and parental involvement factors may differ by race in previous research, the differences within the female sample in this study are minimal. These findings indicate that educators, policy makers, and program leaders should incorporate more inclusive strategies to nurture the identity of female high school students as STEM students and professionals.

References

Addy, S., Engelhardt, W., & Skinner, C. (2013). Basic facts about low-income children (Children under 18 years, 2011). Retrieved from http://www.nccp.org/publications/pdf/text_1074.pdf

American Educational Research Association. (2014). AERA Professional development. Retrieved from http://www.aera.net/

American Psychological Association (APA). (2014). Socioeconomic status. Retrieved from http://www.apa.org/topics/socioeconomic-status/

Armor, D. J. (2001). On family size and intelligence. *American Psychologist*, *56*(6), 521-522. doi: 10.1037/0003-066x.56.6-7.521

Armor, D. J. (2005). Can NCLB close the achievement gap? In A. R. Sadovnik, J. A. O'Day, G. W. Bohrnstedt & K. M. Borman (Eds.), *No Child Left Behind and the reduction of the achievement gap* (pp. 323-342). New York, NY: Routledge.

Armor, D. J. (2006). Brown and Black-White Achievement. *Academic Questions*, *19*(2), 40-46.

Aron, A., & Aron, E. N. (1999). *Statistics for psychology* (2nd ed.). Upper Saddle River, NJ: Prentice Hall.

Aronson, J. (2002). Stereotype threat: Contending and coping with unnerving expectations. In J. Aronson (Ed.), *Improving academic achievement: Impact of psychological factors on education* (pp. 279–301). San Diego, CA: Academic Press.

Bakker, J., Denessen, E., & Brus-Laeven, M. (2007). Socio-economic background, parental involvement and teacher perceptions of these in relation to pupil

achievement. *Educational Studies, 33*(2), 177-192. doi: 10.1080/03055690601068345

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall

Bandura, A. (1989). Social cognitive theory. In R. Vasta (Ed.), *Annals of child development. Vol. 6. Six theories of child development* (pp. 1-60). Greenwich, CT: JAI Press.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: Freeman.

Beckert, T. (2008). Narrowing the achievement gap: Strategies for educating Latino, Black, and Asian students. *Journal of Youth & Adolescence, 37*(4), 486-487.

Beede, D., Julian, T., Langdon, D., McKittrick, G., Khan, B., & Doms, M. (2011). *Women in STEM: A Gender Gap to Innovation.* Retrieved from U.S. Department of Commerce, Economics and Statistics Administration: http://www.esa.doc.gov/sites/default/files/reports/documents/womeninstemagaptoinnovation8311.pdf

Berry, R. Q. (2008). Access to upper-level mathematics: The stories of successful African American middle school boys. *Journal for Research in Mathematics Education, 39*(5), 464-488.

Bix, A.S. (2004). From “engineeresses” to “girl engineers” to “good engineers”: A history of Women’s U.S. engineering education. *NWSA Journal, 16*, 27-49.

Blickenstaff, J. C. (2005). Women and science careers: Leaky pipeline or gender filter? *Gender and Education, 17*(4), 369–386.

Brainard, S., & Carlin, L. (1998). A six-year longitudinal study of undergraduate women in engineering and science. *Journal of Engineering Education*, *87*(4), 369-375.

Brooks-Gunn, J., Klebanov, P. K., Smith, J., Duncan, G. J., & Lee, K. (2003). The Black-White test score gap in young children: Contributions of test and family characteristics. *Applied Developmental Science, 7*(4), 239-252. doi: 10.1207/s1532480xads0704_3

Board of Science Education (2011). *Successful k-12 STEM education: Identifying effective approaches in science, technology, engineering, and mathematics*. Retrieved from www.nap.edu/catalog/13158.html

Brown-Jeffy, S. (2009). School effects: Examining the race gap in mathematics achievement. *Journal of African American Studies*, *13*(4), 388-405. doi: 10.1007/s12111-008-9056-3

Business-Higher Education Forum. (2002). Investing in people: Developing all of America's talent on campus and in the workplace. Retrievedf rom http://www.bhef.com/publicaitons/pubs.asp

Byrnes, J. P. (2003). Factors predictive of mathematics achievement in White, Black, and Hispanic 12th graders. *Journal of Educational Psychology, 95*(2), 316-326. doi: 10.1037/0022-0663.95.2.316

Campos, D. (2008). An approach to eradicating the achievement gap: Making instruction meaningful. *Black History Bulletin, 71*(1), 25-34.

Carlone, H. B., & Johnson, A. (2007). Understanding the science experiences of women of color: Science identity as an analytic lens. *Journal of Research in Science Teaching, 44*, 1187–1218.

Carpenter Ii, D. M., Ramirez, A., & Severn, L. (2006). Gap or gaps: Challenging the singular definition of the achievement gap. *Education & Urban Society*, *39*(1), 113-127.

Chall, J. S. (1996). American reading achievement: Should we worry? *Research in the Teaching of English, 30*(3), 303-310.

Chan, Y., Hui, D., Dickinson, A. R., Chu, D., Cheng, D. K., Cheung, E., Luk, K. (2010). Engineering outreach: A successful initiative with gifted students in science and technology in Hong Kong. *IEEE Transactions on Education*, *53*, 158-171.

Cheung, C., & Pomerantz, E. M. (2012). Why does parents' involvement in children's learning enhance children’s achievement? The role of parent-oriented motivation. *Journal of Educational Psychology, 104, 820-832.*

Chubb, J. E., & Loveless, T. (2002). *Bridging the achievement gap*. Washington, DC: Brookings Institution Press.

Cobb, P., Gresalfi, M., & Hodge, L.L. (2009). An Interpretive Scheme for Analyzing the Identities That Students Develop in Mathematics Classrooms. *Journal for Research in Mathematics Education*, *40*(1), 40-68.

Cohen, J. (1988). *Statistical power analysis for the behavior sciences* (2nd ed.). New York, NY: Psychology Press.

Cohen, B. H. (2001). *Explaining psychological statistics* (2nd ed.). New York, NY: Wiley.

Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

Cole & Espinoza (2008). Examining the Academic Success of Latino Students in Science Technology Engineering and Mathematics (STEM) Majors. *Journal of College Student Development, 49*(4), 285-300.

Coleman, J. S., Campbell, E. Q., Hobson, C. J., McPartland, F., Mood, A. M., & Weinfeld, F. D. (1966). *Equality of educational opportunity*. Washington, DC: U.S. Government Printing Office.

de Boer, H., Bosker, R.J., & van der Werf, M.P.C. (2010). Sustainability of teacher expectation bias effects on long-term student performance. *Journal of Educational Psychology, 102*(1), 168-179.

Deci, E.L. & Ryan, R.M. (1995). Human autonomy: The basis for true self-esteem. In M. Kernis (Ed.), *Efficacy, agency, and self-esteem* (pp. 31-49). New York, NY: Plenum Publishing Co.

Desimone, L. M., & Long, D. (2010). Teacher effects and the achievement gap: Do teacher and teaching quality influence the achievement gap between Black and White and high- and low-ses students in the early grades?. *Teachers College Record, 112*(12), 3024-3075.

Duncan-Andrade, J. M. R. (2009). Note to educators: Hope required when growing roses in concrete. *Harvard Educational Review, 79*(2), 181-194.

Eccles, J.S., Adler, T.F., Futterman, R., Goff, S.B., Kaczala, C.M., & Meece, J.L. (1983). Expectancies, values and academic behaviors. In J.T. Spence (Ed.), *Achievement and achievement motives* (pp. 75-146). San Francisco, CA: Freeman.

Eccles, J.S., Wigfield, A., Harold, R.D., & Blumenfeld, P. (1993). Age and gender differences in children's self- and task perceptions during elementary school. *Child Development, 64*, 830-847.

Ecnomics and Statistics Administration. (2011, July 14). New Commerce Department Report Shows fast-growing STEM jobs offer higher pay, lower unemployment. Retrieved from http://www.commerce.gov/news/pressreleases/2011/07/14/new-commerce-department-report-shows-fst-growing-stem-jobsoffer-hig

Else-Quest, N.M., Linn, M., Hyde, J. (2011). Cross-national patterns of gender differences in mathematics: A meta-analysis. *Psychological Bulletin, 136*(1), 103-127.

Emdin, C. (2011). *Five reasons why your child won't be a scientist (and what you can do about it).* Huffington Post. Retrieved fromhttp://www.huffingtonpost.com/christopher-emdin/children science_b_1081642.html

Engberg, M. & Gilbert, A. (2014). The counseling opportunity structure: Examining correlates of four-year college-going rates. *Research in Higher Education, 55*(3), pp. 219-244.

Epstein, J. L. (2005). Attainable goals? The spirit and letter of the No Child Left Behind Act on parental involvement. *Sociology of Education, 78*(2), 179-182.

Fan, W. (2011). Social influences, school motivation and gender differences: an application of the expectancy-value theory. *Educational Psychology: An International Journal of Experimental Educational Psychology, 31*(2), 157-175.

Fantuzzo, J., McWayne, C., Perry, M. A., & Childs, S. (2004). Multiple dimensions of family involvement and their relations to behavioral and learning competencies for urban, low-income children. *School Psychology Review, 33*(4), 467-480.

Ferguson, R. F. (2003). Teachers' perceptions and expectations and the Black-White test score gap. *Urban Education, 38*(4), 460-507. doi:10.1177/0042085903038004006

Frederickson, N., & Petrides, K. V. (2008). Ethnic, gender, and socio-economic group differences in academic performance and secondary school selection: A longitudinal analysis. *Learning and Individual Differences, 18*, 144-151.

Gamoran, A., & Long, D. A. (2006). *Equality of educational opportunity: A 40-year retrospective*. (Doctoral dissertation, Wisconsin Center for Education Research). Retrieved from http://www.wcer.wisc.edu/publications/workingPapers/papers.php

Ganley, C. M., Mingle, L. A., Ryan, A. M., Ryan, K., Vasilyeva, M., & Perry, M. (2013). An examination of stereotype threat effects on girls' mathematics performance. *Developmental Psychology*, *49*(10), 1886-1897. doi:10.1037/a0031412

Gonzalez, J.C. (2006). Academic socialization experiences of Latina doctoral students: A qualitative understanding of support systems that aid and challenges that hinder the process. *Journal of Hispanic Higher Education, 5*(4), 347-365.

Greenwood Dictionary of Education. (2011). Pygmalion effect. Retrieved from Credo Reference Collections, EBSCOhost.

Guyll, M., Madon, S., Prieto, L., & Scherr, K. C. (2010). The potential roles of self-fulfilling prophecies, stigma consciousness, and stereotype threat in linking Latino/a ethnicity and educational outcomes. *Journal of Social Issues, 66*, 113-130.

Hackett, G., & Betz, N.E. (1989). An Exploration of the Mathematics Self-Efficacy/Mathematics Performance Correspondence. *Journal for Research in Mathematics Education*, *20*(3): 261-273.

Halpern, D.F., Bendow, C.P., Geary, D.C., Gur, R.C., Hyde, J.S., & Gernsbacher, M.A. (2007). The science of sex differences in science and mathematics. *Psychological Science in Public Interest, 8*, 1-51.

Heller, K. A., & Perleth, C. (2008). The Munich High Ability Test Battery (MHBT): A multidimensional, multimethod approach. *Psychology Science*, *50*, 173-188.

Hidi, S. (2000). An interest researcher's perspective: The effects of extrinsic and intrinsic factors on motivation. In C. Sansone & J. M. Harackiewicz (Eds.), *Intrinsic and extrinsic motivation* (pp. 309-339). San Diego, CA: Academic Press.

Holland, D., & Lave, J.(Eds.) (2001). *History in person: Enduring struggles, contentious practice, intimate identities*. Santa Fe: School of American Research Press.

Howard, T. C. (2010). *Why race and culture matter in schools: Closing the achievement gap in America's classrooms*. New York, N.Y.: Teachers College Press.

Howard, T. C., & Reynolds, R. (2008). Examining parent involvement in reversing the underachievement of African American students in middle-class schools. *Educational Foundations, 22*(1-2), 79-98.

Howitt, D. & Cramer, D. (2014). *Introduction to SPSS statistics in psychology* (6th ed). Upper Saddle River, NJ: Pearson Education.

Hughes, J. N., Gleason, K. A., & Zhang, D. (2005). Relationship influences on teachers' perceptions of academic competence in academically at-risk minority and

majority first grade students. *Journal of School Psychology, 43*, 303-320. doi: 10.1016/j.jsp.2005.07.001

Humes, K. R., Jones, N.A., & Ramirez, R.R. (2011). *Overview of race and Hispanic origin: 2010*. Washington, DC: U.S. Census Bureau.

HyperStat Online Statistics Textbook. (2013). Normal distribution. Retrieved from http://davidmlane.com/hyperstat/index.html

Ingels, S. J., Pratt, D. J., Herget, D. R., Burns, L. J., Dever, J. A., Rodgers, J. E., Leinwand, S. (2011). *High School Longitudinal Study of 2009 (HSLS:09), Base-Year Data File Documentation* (NCES 2011-328). Washington, DC: National Center for Education Statistics. Retrieved from http://nces.ed.gov/pubsearch

Jeynes, W. H. (2003). A meta-analysis: The effects of parental involvement on minority children's academic achievement. *Education and Urban Society, 35*(2), 202-218.

Jeynes, W. H. (2007). The relationship between parental involvement and urban secondary school student academic achievement: A meta-analysis. *Urban Education, 42*(1), 82-110.

Keller, J. (2007). Stereotype threat in classroom settings: The interaction effect of domain identification, task difficulty and stereotype threat on female students' math performance. *British Journal of Educational Psychology, 77*(2), 323-338.

Kellow, J. T., & Jones, B. D. (2008). The effects of stereotypes on the achievement gap: Reexamining the academic performance of African American high school students. *Journal of Black Psychology, 34*(1), 94-120.

Kiefer, A. M., & Sekaquaptewa. (2007). Implicit stereotypes and women's math performance: How implicit gender-math stereotypes influence women's

susceptibility to stereotype threat. *Journal of Experimental Social Psychology, 43*(5), 825-832.

Krapp, A. (2002). Structural and dynamic aspects of interest development: Theoretical considerations from an ontogenetic perspective. *Learning and Instruction*, *12,* 383-409.

Laerd Statistics. (2013). Hierarchical multiple regression in SPSS. Retrieved from https://statistics.laerd.com/premium/hmr/hierarchical-multiple-regression-in-spss.php

Landgraf, L., Peters, P., & Salmons-Stephens, T. (2008). *Recruitment and retention of women in STEM: Effectiveness of current outreach programs at University of Wisconsin Platteville.* Paper presented at the 2008 ASEE North Midwest Sectional Conference, Platteville, WI.

Leaper, C., Farkas, T., & Brown, C. (2012). Adolescent girls' experiences and gender-related beliefs in relation to their motivation in math/science and English. *Journal of Youth and Adolescence*, *41*(3), 268-282.

Legewie, J., & DiPrete, T. A. (2011). *High school environments, stem orientations, and the gender gap in science and engineering degrees.* Retrieved from http://ssrn.com/abstract=2008733

Linnehan, F., Weer, C. H., & Stonely, P. (2011). High school guidance counselor recommendations: The role of student race, socioeconomic status, and academic performance. *Journal of Applied Social Psychology, 41*(3), 536-558.

Levitt, S. D., & Fryer, R. G. (2004). Falling behind: New evidence on the Black-White achievement gap. *Education Next, 4*(4), 64-71.

Lubinski, D., & Benbow, C. P. (2006). Study of mathematical precocious youth after 35 years. *Perspectives on Psychological Science*, *1,* 316-345.

Mandara, J., Varner, F., Greene, N., & Richman, S. (2009). Intergenerational family predictors of the Black-White achievement gap. *Journal of Educational Psychology, 101*(4), 867-878. doi: 10.1037/a0016644

Martin, D. B. (2000). *Mathematics success and failure among African-American youth: The roles of sociohistorical context, community forces, school influence, and individual agency*. Mahwah, NJ: Lawrence Erlbaum.

Mickelson, R. A., Bottia, M., & Southworth, S. (2008). *School choice and segregation by race, class, and achievement.*Boulder, CO: National Education Policy Center.

Mujis, D. (2011). *Doing Quantitative Research in Education with SPSS.* (2nd ed.). Thousand Oaks, CA: Sage.

National Research Council (NRC). (2012). *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*. Washington, DC: The National Academies Press.

National Science Board. 2012. Science and Engineering Indicators 2012. Arlington VA: National Science Foundation (NSB 12-01).

Nichols, R. C. (1967). The coleman report: An inadequate study but the best we have so far. *Phi Delta Kappan, 48*(10), 527-530.

Oh, R. (2009). On account of race or color: Race as corporation and the original understanding of race. *Albany Law Review. 72*(4), 1027-1040.

Ornstein, A. (2010). Achievement gaps in education. *Society,* pp. 424-429. Retrieved from http://libproxy.chapman.edu/login?url=http://search.ebscohost.com/login.

aspx?direct=true&AuthType=ip,uid&db=aph&AN=53479940&site=eds-live

Orr, A. J. (2003). Black-White differences in achievement: The importance of wealth. *Sociology of Education, 76*(4), 281-304.

Pedhazur, E. J. (1982). *Multiple regression in behavioral research: Explanation and prediction* (2nd ed.). New York, NY: Holt, Rinehart, and Winston.

Pallant, J. (2013). *SPSS Survival Manual*. (5th ed.). New York, NY: McGraw-Hill.

Phillips, M., Crouse, J., & Ralph, J. (1998). Does the Black–White test score gap widen after children enter school? In C. Jencks & M. Phillips (Eds.), *The Black–White test score gap.* (pp. 229-272). Washington, DC: Brookings Institution Press.

Rathbun, A., West, J., & Walston, J. (2005). *Relationships between family risks and children's reading and mathematics growth from kindergarten through third grade*. Paper presented at the Annual Meeting of the American Educational Research Association, Montreal, CA. Retrieved from http://www.eric.ed.gov/PDFS/ED490454.pdf

Reardon, S.F., Yun, J.T., & Kurlaender, M. (2006). Implications of income-based school assignment policies for racial school segregation. *Educational Evaluation and Policy Analysis*, *28,*49–75.

Reeves, D.B. (2011). *Finding your leadership focus: what matters most for student results*, New York: Teachers College Press.

Reiss, S. (2012). High-school math in the cloud: North Carolina project strengthens students’ math skills using cloud computing and videos. Retrieved from http://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=124342&WT.mc_id=USNSF_1

Robnett, R. D., & Leaper, C. (2013). Friendship groups, personal motivation, and gender in relation to high school students' STEM career interest. *Journal of Research on Adolescence, 23*, 652-664.

Rosenthal, R., & Jacobson, L. (1968). *Pygmalion in the classroom; teacher expectation and pupils' intellectual development*. New York, NY: Holt.

Ryan, K. E., & Ryan, A. M. (2005). Psychological processes underlying stereotype threat and standardized math test performance. *Educational Psychologist, 40*(1), 53-63.

Scales, P. C., & Leffert, N. (2004). *Developmental assets: A synthesis of the scientific research on adolescent development* (2nd ed.). Minneapolis, MN: Search Institute.

Schaefer, R. (2011). *Racial and Ethnic Groups*. Boston, MA: Pearson Education.

Schiefele, U., Krapp, A., & Winteler, A. (1992). Interest as a predictor of academic achieve- ment: A meta-analysis of research. In K. A. Renninger, S. Hidi, & A. Krapp (Eds.), *The role of interest in learning and development* (pp. 183-212). Hillsdale, NJ: Lawrence Erlbaum.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: Theory, research, and applications*. Upper Saddle River, NJ: Pearson.

Sfard, A. & Prusak, A. (2005). Telling identities: In search of an analytic tool for investigating learning as a culturally shaped activity. Educational Researcher, 34(4), 14-22.

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417-453.

Sung, H., Padilla, A. M., & Silva, D. M. (2006). Foreign language education, academic performance, and socioeconomic status: A study of California school. *Foreign Language Annals, 39*(1), 115-130.

Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology, 69*, 797-811.

Stuart, E.A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science 25*(1): 1–21.

Tabachnick, B.G. & Fidell, L.S. (2013). Using multivariate statistics (6th ed). Boston: Pearson, Education.

Thoemmes, F. (2012). *Propensity score matching in SPSS*. Unpublished manuscript, Center for Educational Science and Psychology, University of Tübingen, Tübingen, Germany.

Thoemmes, F., & Kim, E. S. (2011). A Systematic Review of Propensity Score Methods in the Social Sciences. *Multivariate Behavioral Research, 46,* 90-118.

Trouilloud, D. O., Sarrazin, P. G., Martinek, T. J., & Guillet, E. (2002). The influence of teacher expectations on student achievement in physical education classes: Pygmalion revisited. *European Journal of Social Psychology, 32*(5), 591-607. doi: 10.1002/ejsp.109

Unnever, J. D., Kerckhoff, A. C., & Robinson, T. J. (2000). District variations in educational resources and student outcomes. *Economics of Education Review, 19*, 245-259. doi: 10.1016/s0272-7757(99)00043-6

U.S. Department of Education, National Assessment Governing Board. (2010). *Science framework for the 2011 National Assessment of Educational Progress*. Retrieved from National Assessment Governing Board website: http://nces.ed.gov/nationsreportcard/

Voss, J. F., & Schauble, L. (1992). Is interest educationally interesting? An interest-related model of learning. In K. Renninger, S. Hidi, & A. Krapp (Eds.), *The role of interest in learning and development* (pp. 101-120). Hillsdale, NJ: Lawrence Erlbaum.

Walker, E. N. (2006). Urban high school students' academic communities and their effects on mathematics success. *American Educational Research Journal, 43*(1), 43-73.

Wenglinsky, H. (2004). The link between instructional practice and the racial gap in middle schools. *Research in Middle Level Education Online, 28*(1), 1-18.

Wigfield, A., & Eccles, J. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*, 265-310.

Wigfield, A., Eccles, J.S., & Pintrich, P.R. (1996). Development between the ages of 11 and 25. In R.C. Calfee & D.C. Berliner (Eds.), *Handbook of educational psychology* (pp. 148-185). New York, NY: Prentice Hall International.

Williams, A. (2011). A call for change: Narrowing the achievement gap between White and minority Students. *Clearing House: A Journal of Educational Strategies, Issues and Ideas, 84*(2), 65-71.

Wylie, A., Jakobsen, J.R., & Fosado, G. (2007). Women, work, and the academy: Strategies for responding to ‘post-civil rights era’ gender discrimination. Report

based on the Virginia C. Gildersleeve Conference at the Barnard Center for Research on Women.

Zeldin, A. L., & Pajares, F. (2000). Against the odds: Self-efficacy beliefs of women in mathematical, scientific, and technological careers. *American Educational Research Journal, 37*(1), 215-246.

Table 1

Variables HSLS:09/12 Data File

HSLS Code	Variable Type	Variable Name	Variable Description
X2MTHEFF	Independent	Mathematics Self-Efficacy	Scale of 11th graders' self-reported mathematics self-efficacy
X2MTHINT	Independent	Mathematics Interest	Scale of student's interest in fall 2009 math course
X2MTHID	Independent	Mathematics Identity	Scale of 11th graders' self-reported mathematics identity
PINV	Independent	Parental Involvement	Scale of parental involvement, as reported by parent(s)
X2SES	Independent	Socio-economic Status	Socio-economic status composite based on self-reported data (ex. income, occupation, and education)
X2TXMTH	Dependent	Mathematics Theta Score	Mathematics Theta (ability) scores

Table 2

Three Component Matrix for Parental Involvement Scale

	Component		
	1	2	3
P2 B14D How often discussed careers he/she might be interested in	.793		
P2 B14C How often discussed applying to college/other schools after high school	.748		-.319
P2 B14B How often discussed preparing for college entrance exams	.739		
P2 B14A How often discussed selecting courses or programs at school	.731		
P2 B14F How often discussed community/national/world events	.700		
P2 B14E How often discussed job that he/she might want to take after high school	.690		
P2 B14G How often discussed things that were troubling him/her	.630		
P2 B09A Confidence in helping with math homework 2011-2012/when last enrolled		.892	
P2 B09B Confidence in helping with science homework 2011-2012/when last enrolled		.860	
P2 B15 How often contacted teen's school since start of 2011-2012 school year	.397		.712
P2 B08 How often helped teenager with homework	.456		.487
Extraction Method: Principal Component Analysis.			
a. 3 components extracted.			

Table 3

Two Component Matrix[a] for Parental Involvement Scale

	Component	
	1	2
P2 B14D How often discussed careers he/she might be interested in	.793	
P2 B14C How often discussed applying to college/other schools after high school	.748	
P2 B14B How often discussed preparing for college entrance exams	.739	
P2 B14A How often discussed selecting courses or programs at school	.731	
P2 B14F How often discussed community/national/world events	.700	
P2 B14E How often discussed job that he/she might want to take after high school	.690	
P2 B14G How often discussed things that were troubling him/her	.630	
P2 B08 How often helped teenager with homework	.456	
P2 B15 How often contacted teen's school since start of 2011-2012 school year	.397	
P2 B09A Confidence in helping with math homework 2011-2012/when last enrolled		.892
P2 B09B Confidence in helping with science homework 2011-2012/when last enrolled		.860
Extraction Method: Principal Component Analysis.		
a. 2 components extracted.		

Table 4

Demographic Data for Female High school Students in the HSLS:09/12 (N=11,493)

Variable	N	Percent in Female Sample
Race		
American Indian/Alaska Native	80	.7%
Asian	934	8.1%
Black/African-American	1,170	10.2%
Hispanic	1,910	16.7%
More than one race, non-Hispanic	986	8.6%
Native Hawaiian/Pacific Islander	58	.5%
White	6,355	55.3%
Parent 1: Highest level of education		
Less than high school	835	7.3%
High school diploma, GED, or alternative HS credential	3,791	33%
Certificate/diploma from school providing occupational training	434	3.8%
Associate's Degree	1,638	14.3%
Bachelor's Degree	2,356	20.5%
Master's Degree	970	8.4%
PhD/MD/Law/other high level professional degree	347	3%
Missing responses	1,122	9.8%
Parent 2: Highest level of education		
Less than high school	810	7%
High school diploma, GED, or alternative HS credential	3,312	28.8%
Certificate/diploma from school providing occupational training	307	2.7%
Associate's Degree	998	8.7%
Bachelor's Degree	1,627	14.2%
Master's Degree	608	5.3%
PhD/MD/Law/other high level professional degree	369	3.2%
Missing, oregitimate skip (possible single parent home)	1,122 2,340	9.8% 20.4%
School Geographic Region		
Northeast	1,767	15.4%
Midwest	2,802	24.4%
South	4,293	37.4%
West	1,866	16.2%
Missing	113	1%
Not Applicable	652	5.7%

Table 5

Demographic Data for the Study Sample (N=3,938)

Variable	N	Percent in Study Sample
Race		
American Indian/Alaska Native	18	.5%
Asian	302	7.7%
Black/African-American	436	11.1%
Hispanic	624	15.9%
More than one race, non-Hispanic	334	8.5%
Native Hawaiian/Pacific Islander	21	.5%
White	2,203	55.9%
Parent 1: Highest level of education		
Less than high school	334	8.5%
High school diploma, GED, or alternative HS credential	1,322	33.6%
Certificate/diploma from school providing occupational training	222	5.6%
Associate's Degree	582	14.8%
Bachelor's Degree	927	23.5%
Master's Degree	412	10.5%
PhD/MD/Law/other high level professional degree	139	3.5%
Parent 2: Highest level of education		
Less than high school	318	8.1%
High school diploma, GED, or alternative HS credential	1,215	30.9%
Certificate/diploma from school providing occupational training	151	3.8%
Associate's Degree	351	8.9%
Bachelor's Degree	647	16.4%
Master's Degree	230	5.8%
PhD/MD/Law/other high level professional degree	147	3.7%
Missing, or legitimate skip (possible single parent home)	879	22.3%
School Geographic Region		
Northeast	640	16.3%
Midwest	951	24.1%
South	1,523	38.7%
West	685	17.4%
Missing	47	1.2%
Not Applicable	92	2.3%

Table 6

Research Questions, Variables, Hypotheses, and Analysis

Research Questions/Hypotheses	IV(s)	DV	Analysis
RQ1: How well do motivation (i.e. self-efficacy, interest, or identity) and parental involvement predict STEM achievement for female high school students? **H1:** Mathematics self-efficacy is a stronger predictor of STEM achievement than mathematics interest for female high school students **H2:** Mathematics self-efficacy is a stronger predictors of STEM achievement than mathematics identity for female high school student H**3:** Mathematics identity is a stronger predictors of STEM achievement than parental involvement for female high school students	• Self-efficacy Scale • Interest Scale • Identity Scale • Parental Inv. Scale • SES	• Math Theta Score	Hierarchical Multiple Regression for all females Block 1: SES (control variable) Block 2: Self-efficacy, Interest, Identity Block 3: Parental Involvement
RQ2: Do motivational factors predict achievement for female high school students, differently, when race is considered? **H4:** Parental involvement is a stronger predictor of STEM achievement for black female high school students, than those of other races	• Self-efficacy Scale • Interest Scale • Identity Scale • Parental Inv. Scale • SES	• Math Theta Score	Hierarchical Multiple Regression (similar blocks noted above) for female students, by race, with variables entered into the model the same as above. Analysis on each group will be run separately for HSLS:09/12.

Table 7

Correlation Matrix for Variables in the Study

		X2 Math theta score	X2 SES Comp.	X2 Scale of math self-efficacy	X2 Scale of interest in fall 2009 math course	X2 Scale of math identity	Parental Inv. Scale (PInv)
Pearson Correlation	X2 Math theta score	-					
	X2 SES composite	.408	-				
	X2 Scale of math self-efficacy	.260	.092	-			
	X2 Scale of interest in fall 2009 math course	.194	.031	.602	-		
	X2 Scale of math identity	.381	.097	.575	.580	-	.101
	Parental Inv. Scale	.247	.351	.095	.091	.101	-
Sig. (1-tailed)	X2 Math theta score	.					
	X2 SES composite	.000	.				
	X2 Scale of math self-efficacy	.000	.000	.			
	X2 Scale of interest in fall 2009 math course	.000	.002	.000	.		
	X2 Scale of math identity	.000	.000	.000	.000	.	.000
	Parental Inv. Scale	.000	.000	.000	.000	.000	.

Table 8

Coefficients[a] for Female High school Students

Model		Un-standardized Coefficients		Standard-ized Coeff.	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero order	Partial	Part	Tol.	VIF
1	(Constant)	.657	.018		36.583	.000					
	X2 SES composite	.603	.024	.408	25.050	.000	.408	.408	.408	1.000	1.000
2	(Constant)	.682	.017		40.754	.000					
	X2 SES composite	.548	.022	.371	24.430	.000	.408	.400	.369	.986	1.014
	X2 Scale of student's math self-efficacy	.067	.022	.061	3.040	.002	.260	.054	.046	.558	1.792
	X2 Scale of student's interest in math course	-.055	.022	-.050	-2.486	.013	.194	-.044	-.038	.554	1.804
	X2 Scale of student's math identity	.363	.021	.338	17.095	.000	.381	.292	.258	.581	1.722
3	(Constant)	.244	.078		3.146	.002					
	X2 SES composite	.501	.024	.339	21.059	.000	.408	.352	.316	.868	1.151
	X2 Scale of student's math self-efficacy	.065	.022	.060	2.988	.003	.260	.053	.045	.558	1.792
	X2 Scale of student's interest in math course	-.060	.022	-.055	-2.750	.006	.194	-.049	-.041	.553	1.807
	X2 Scale of student's math identity	.360	.021	.336	17.049	.000	.381	.291	.256	.581	1.723
	Parental Inv. Scale	.034	.006	.093	5.767	.000	.247	.102	.087	.870	1.150
a. Dependent Variable: X2 Mathematics theta score											

Table 9

Outliers Determined by Casewise Diagnostics[a]

Case Number	Std. Residual	X2 Mathematics theta score	Predicted Value	Residual
1198	-3.147	-1.12	1.7292	-2.85269
2310	3.050	2.24	-.5272	2.76439
4110	-3.030	-1.43	1.3137	-2.74686
4124	-3.155	-1.31	1.5454	-2.85992
5179	3.534	3.95	.7433	3.20333
5252	-3.846	-1.50	1.9849	-3.48661
5367	-3.862	-1.50	2.0029	-3.50067
5431	-3.279	-1.28	1.6909	-2.97215
5984	3.078	4.06	1.2655	2.79050
6648	-3.315	-1.43	1.5780	-3.00536
a. Dependent Variable: X2 Mathematics theta score				

Table 10

HMR Model Summary[d] for Female High school Students

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.408[a]	.167	.166	.99997	.167	627.521	1	3137	.000
2	.535[b]	.287	.286	.92569	.120	175.548	3	3134	.000
3	.542[c]	.294	.293	.92096	.007	33.263	1	3133	.000

a. Predictors: (Constant), X2 Socio-economic status composite

b. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

d. Dependent Variable: X2 Mathematics theta score

Table 11

ANOVA for HMR Model of Female High school Students

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	627.482	1	627.482	627.521	.000[b]
	Residual	3136.805	3137	1.000		
	Total	3764.286	3138			
2	Regression	1078.762	4	269.690	314.728	.000[c]
	Residual	2685.524	3134	.857		
	Total	3764.286	3138			
3	Regression	1106.974	5	221.395	261.027	.000[d]
	Residual	2657.312	3133	.848		
	Total	3764.286	3138			

a. Dependent Variable: X2 Mathematics theta score

b. Predictors: (Constant), X2 Socio-economic status composite

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

d. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

Table 12

HMR Model Summary for Black/African American Female Students

Model	R X2 Student's race/ ethnicity-composite Black/ African-American, non-Hispanic (Selected)	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.333[a]	.111	.108	.92714	.111	41.120	1	330	.000
2	.416[b]	.173	.163	.89837	.062	8.159	3	327	.000
3	.434[c]	.188	.176	.89140	.015	6.133	1	326	.014

a. Predictors: (Constant), X2 Socio-economic status composite

b. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, X2 Scale of student's interest in fall 2009 math course

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, X2 Scale of student's interest in fall 2009 math course, Parental Involvement Scale

d. Unless noted otherwise, statistics are based only on cases for which X2 Student's race/ethnicity-composite = Black/African-American, non-Hispanic.

e. Dependent Variable: X2 Mathematics theta score

Table 13

ANOVA[a,b] for Black/African American Female Students

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35.346	1	35.346	41.120	.000[c]
	Residual	283.667	330	.860		
	Total	319.013	331			
2	Regression	55.102	4	13.775	17.069	.000[d]
	Residual	263.911	327	.807		
	Total	319.013	331			
3	Regression	59.975	5	11.995	15.096	.000[e]
	Residual	259.038	326	.795		
	Total	319.013	331			
a. Dependent Variable: X2 Mathematics theta score						
b. Selecting only cases for which X2 Student's race/ethnicity-composite = Black/African-American, non-Hispanic						
c. Predictors: (Constant), X2 Socio-economic status composite						
d. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, X2 Scale of student's interest in fall 2009 math course						
e. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, X2 Scale of student's interest in fall 2009 math course, Parental Involvement Scale						

Table 14

Coefficients[a,b] for Black/African American Female Students

Model		Un -standardized Coefficients		Standard -ized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	T	Sig.	Zero-order	Partial	Part	Tol.	VIF
1	(Constant)	.292	.052		5.640	.000					
	X2 SES composite	.465	.073	.333	6.412	.000	.333	.333	.333	1.000	1.000
2	(Constant)	.300	.051		5.889	.000					
	X2 SES composite	.460	.071	.329	6.498	.000	.333	.338	.327	.989	1.011
	X2 Scale of math self-efficacy	.035	.066	.034	.521	.603	.164	.029	.026	.609	1.641
	X2 Scale of interest in math	-.024	.065	-.024	-.363	.717	.113	-.020	-.018	.586	1.705
	X2 Scale of math identity	.232	.061	.243	3.775	.000	.249	.204	.190	.613	1.633
3	(Constant)	-.264	.233		-1.132	.259					
	X2 SES composite	.413	.073	.295	5.684	.000	.333	.300	.284	.923	1.084
	X2 Scale of math self-efficacy	.042	.066	.041	.640	.522	.164	.035	.032	.608	1.644
	X2 Scale of interest in math	-.016	.065	-.016	-.244	.807	.113	-.014	-.012	.585	1.709
	X2 Scale of math identity	.211	.062	.220	3.424	.001	.249	.186	.171	.601	1.665
	Parental Inv Scale	.042	.017	.129	2.476	.014	.230	.136	.124	.915	1.093
a. Dependent Variable: X2 Mathematics theta score											
b. Selecting only cases for which X2 Student's race/ethnicity-composite = Black/African-American, non-Hispanic											

Table 15

HMR Model Summary[d,e] for European American Female Students

Model	R X2 Student's race/ Ethnicity comp. White, non-Hispanic	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.397[a]	.157	.157	.97913	.157	327.979	1	1756	.000
2	.545[b]	.297	.295	.89518	.139	115.928	3	1753	.000
3	.565[c]	.319	.317	.88109	.022	57.539	1	1752	.000

a. Predictors: (Constant), X2 Socio-economic status composite

b. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

d. Unless noted otherwise, statistics are based only on cases for which X2 Student's race/ethnicity-composite = White, non-Hispanic.

e. Dependent Variable: X2 Mathematics theta score

Table 16

ANOVA[a,b] for White Female High school Students

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	314.432	1	314.432	327.979	.000[c]
	Residual	1683.469	1756	.959		
	Total	1997.901	1757			
2	Regression	593.129	4	148.282	185.040	.000[d]
	Residual	1404.771	1753	.801		
	Total	1997.901	1757			
3	Regression	637.798	5	127.560	164.314	.000[e]
	Residual	1360.103	1752	.776		
	Total	1997.901	1757			

a. Dependent Variable: X2 Mathematics theta score

b. Selecting only cases for which X2 Student's race/ethnicity-composite = White, non-Hispanic

c. Predictors: (Constant), X2 Socio-economic status composite

d. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

e. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

Table 17

Coefficients[a,b] for European American Female Students

Model		Unstandardized Coefficients		Stand. Coeff.			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tol.	VIF
1	(Constant)	.667	.024		27.564	.000					
	X2 SES composite	.593	.033	.397	18.110	.000	.397	.397	.397	1.000	1.000
2	(Constant)	.715	.022		31.934	.000					
	X2 SES composite	.518	.030	.347	17.138	.000	.397	.379	.343	.980	1.021
	X2 Scale of math self-efficacy	.081	.028	.077	2.833	.005	.294	.068	.057	.540	1.851
	X2 Scale of interest in math	-.069	.029	-.065	-2.353	.019	.226	-.056	-.047	.533	1.876
	X2 Scale of math identity	.377	.028	.365	13.653	.000	.414	.310	.273	.562	1.779
3	(Constant)	-.053	.104		-.508	.612					
	X2 SES composite	.439	.032	.294	13.919	.000	.397	.316	.274	.872	1.146
	X2 Scale of math self-efficacy	.080	.028	.076	2.843	.005	.294	.068	.056	.540	1.851
	X2 Scale interest in math	-.084	.029	-.079	-2.907	.004	.226	-.069	-.057	.531	1.885
	X2 Scale of math identity	.375	.027	.363	13.800	.000	.414	.313	.272	.562	1.779
	Parental Inv Scale	.059	.008	.160	7.585	.000	.298	.178	.150	.875	1.143
a. Dependent Variable: X2 Mathematics theta score											
b. Selecting only cases for which X2 Student's race/ethnicity-composite = White, non-Hispanic											

Table 18

HMR Model Summary[d,e] for Hispanic/Latin American Female Students

Model	R X2 Student's race/ethnicity-composite = Hispanic, race specified (Selected)	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.319[a]	.102	.100	.94557	.102	52.024	1	460	.000
2	.450[b]	.202	.195	.89387	.101	19.248	3	457	.000
3	.454[c]	.206	.197	.89281	.004	2.090	1	456	.149

a. Predictors: (Constant), X2 Socio-economic status composite

b. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics self-efficacy

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

d. Unless noted otherwise, statistics are based only on cases for which X2 Student's race/ethnicity-composite = Hispanic, race specified.

e. Dependent Variable: X2 Mathematics theta score

Table 19

ANOVA[a,b] for Hispanic/Latin American Female Students

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	46.514	1	46.514	52.024	.000[c]
	Residual	411.283	460	.894		
	Total	457.798	461			
2	Regression	92.651	4	23.163	28.989	.000[d]
	Residual	365.146	457	.799		
	Total	457.798	461			
3	Regression	94.317	5	18.863	23.665	.000[e]
	Residual	363.481	456	.797		
	Total	457.798	461			
a. Dependent Variable: X2 Mathematics theta score						
b. Selecting only cases for which X2 Student's race/ethnicity-composite = Hispanic, race specified						
c. Predictors: (Constant), X2 Socio-economic status composite						
d. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics self-efficacy						
e. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's mathematics identity, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale						

Table 20

Coefficients[a,b] for Hispanic/Latin Americn Female Students

Model		Unstandardized Coefficients		Standardized Coeff.	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tol.	VIF
1	(Constant)	.520	.047		11.120	.000					
	X2 SES composite	.456	.063	.319	7.213	.000	.319	.319	.319	1.000	1.000
2	(Constant)	.555	.045		12.409	.000					
	X2 SES composite	.435	.060	.305	7.252	.000	.319	.321	.303	.990	1.010
	X2 Scale of math self-efficacy	.086	.057	.084	1.516	.130	.235	.071	.063	.567	1.764
	X2 Scale of interest in math course	-.055	.055	-.055	-1.001	.317	.148	-.047	-.042	.577	1.732
	X2 Scale of student's mathematics identity	.296	.054	.294	5.509	.000	.319	.250	.230	.613	1.632
3	(Constant)	.298	.183		1.626	.105					
	X2 SES composite	.402	.064	.281	6.239	.000	.319	.280	.260	.859	1.164
	X2 Scale of math self-efficacy	.082	.057	.080	1.448	.148	.235	.068	.060	.566	1.768
	X2 Scale of interest in math	-.057	.055	-.057	-1.033	.302	.148	-.048	-.043	.577	1.733
	X2 Scale of math identity	.292	.054	.290	5.437	.000	.319	.247	.227	.611	1.636
	Parental Involve Scale	.020	.014	.065	1.446	.149	.207	.068	.060	.851	1.175

a. Dependent Variable: X2 Mathematics theta score

b. Selecting only cases for which X2 Student's race/ethnicity-composite = Hispanic, race specified

Table 21

HMR Model Summary[d,e] for Asian American Female Students

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
	X2 Student's race/ ethnicity-composite = Asian, non-Hispanic (Selected)				R Square Change	F Change	df1	df2	Sig. F Change
1	.412[a]	.170	.167	1.02944	.170	55.589	1	272	.000
2	.530[b]	.280	.270	.96368	.111	13.796	3	269	.000
3	.530[c]	.281	.268	.96510	.001	.212	1	268	.646

a. Predictors: (Constant), X2 Socio-economic status composite

b. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

c. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

d. Unless noted otherwise, statistics are based only on cases for which X2 Student's race/ethnicity-composite = Asian, non-Hispanic.

e. Dependent Variable: X2 Mathematics theta score

Table 22

ANOVA[a,b] for Asian American Female Students

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	58.911	1	58.911	55.589	.000[c]
	Residual	288.251	272	1.060		
	Total	347.162	273			
2	Regression	97.347	4	24.337	26.206	.000[d]
	Residual	249.815	269	.929		
	Total	347.162	273			
3	Regression	97.544	5	19.509	20.945	.000[e]
	Residual	249.618	268	.931		
	Total	347.162	273			

a. Dependent Variable: X2 Mathematics theta score

b. Selecting only cases for which X2 Student's race/ethnicity-composite = Asian, non-Hispanic

c. Predictors: (Constant), X2 Socio-economic status composite

d. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy

e. Predictors: (Constant), X2 Socio-economic status composite, X2 Scale of student's interest in fall 2009 math course, X2 Scale of student's mathematics identity, X2 Scale of student's mathematics self-efficacy, Parental Involvement Scale

Table 23

Coefficients^{a,b} for Asian Female Students

Model		Un-standardized Coefficients		Standard-ized Coeff.	T	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tol.	VIF
1	(Constant)	1.297	.067		19.296	.000					
	X2 SES composite	.566	.076	.412	7.456	.000	.412	.412	.412	1.000	1.000
2	(Constant)	1.188	.067		17.829	.000					
	X2 SES composite	.523	.072	.381	7.315	.000	.412	.407	.378	.987	1.013
	X2 Scale of math self-efficacy	.094	.075	.080	1.260	.209	.242	.077	.065	.664	1.506
	X2 Scale of interest in math	-.088	.074	-.074	-1.186	.237	.120	-.072	-.061	.691	1.447
	X2 Scale of math identity	.374	.074	.320	5.037	.000	.354	.294	.261	.665	1.505
3	(Constant)	1.304	.261		4.988	.000					
	X2 SES composite	.541	.081	.394	6.665	.000	.412	.377	.345	.769	1.300
	X2 Scale of math self-efficacy	.096	.075	.081	1.277	.203	.242	.078	.066	.663	1.509
	X2 Scale of interest in math	-.084	.074	-.071	-1.125	.262	.120	-.069	-.058	.683	1.465
	X2 Scale of math identity	.371	.075	.317	4.959	.000	.354	.290	.257	.658	1.520
	Parental Inv. Scale	-.010	.021	-.027	-.460	.646	.160	-.028	-.024	.768	1.303

a. Dependent Variable: X2 Mathematics theta score

b. Selecting only cases for which X2 Student's race/ethnicity-composite = Asian, non-Hispanic