The purpose of the current study was to discern the effects of three latent constructs – self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement among ninth-grade African American male students. A nationally representative sample from the High School Longitudinal Study of 2009 (HSLS09) was used in the study. Study participants were 697 African American males enrolled in ninth grade in the fall of 2009 across the United States. Structural Equation Modeling (SEM) analytical procedures were performed to test the hypothesized relationships of Bandura’s social cognitive theory (SCT) theoretical assumptions.

The results indicate that the three latent variables directly or indirectly were related to Algebra I achievement among ninth grade African American male students. Moreover, the results revealed that self-efficacy and student-teacher relationships constructs had direct significant impact on Algebra I academic performance; nonetheless, the relationships were not strong. These two latent variables had small effect sizes of 5% and 1%, respectively. Combined, self-efficacy, academic engagement, and student-teacher relationships explained only 8% of the variance in the Algebra I achievement among African American males across the United States ($R^2=.08$). The magnitude effect of these factors on Algebra I achievement was minimal.

Overall, these findings suggest that the self-efficacy and student-teacher relationships latent variables had a negligible effect as predictors of Algebra I academic success among ninth grade African American male students. A summary of the results are presented and future research is recommended.
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CHAPTER 1

INTRODUCTION

The United States has veered from an industrial-oriented to a service, information, and technology-based economy in the past 50 years. This economic shift has overwhelmed the education system to provide advanced skills and educational credentials for the economy to thrive (Wimberly, 2002). According to Donnor and Shockley (2010), “The economic vitality of the United States in the 21st century is contingent upon the productivity of well-educated people and the steady stream of scientific and technical innovations they produce” (p. 44).

Mathematics is a fundamental subject in today’s ever-changing economy (National Council of Teachers of Mathematics [NCTM], 2000). The NCTM (2000) upheld “the need to understand and be able to use mathematics in everyday life has never been greater and will continue to increase” (p. 1). Thus, advanced skills in math and science are indispensable to succeed in today’s economy. Although mathematics and science are vital, the United States lags behind other industrialized nations in academic performance of these two subjects (Museus, Palmer, Davis, & Maramba, 2011).

A current educational outcome is that not all children have adequate access to the education required to be successful in math and science. This lack of access is a concern among educators and policy makers. Specifically, minority students of color who attend schools that are ill equipped to teach advanced math classes are discouraged from pursuing advanced math and science courses (Museus et al., 2011). This lack of adequate math skills among minority students has intensified the shortage of highly qualified minority students pursuing courses and careers in science, technology, engineering, and math (STEM) (Museus et al., 2011). Simply
stated, a need exists to increase minority representation in STEM-related fields to ensure an ethnically and racially diverse technologically literate workforce in the United States.

African American male students in the United States lag behind their counterparts in academic achievement (Hamlet, 2012), graduation rate (Schott Foundation for Public Education [SFPE], 2012), and STEM college enrollment and careers (Museus et al., 2011). A fundamental reason for this underrepresentation in STEM careers is that a significant number of African American male students drop out of Algebra I classes (Gomez, 2012). Similarly, these students perform poorly on math competency tests and do not acquire the skills in math and science that are critical to realizing better economic opportunities (Gomez, 2012). Quite simply, African Americans and other minority groups must acquire advanced skills, knowledge, and educational credentials to thrive in this rapidly changing global economy (Wimberly, 2002).

Hamlet (2012) reported that African American male students lag behind their peers in almost all educational indicators and have low standardized test scores and high school dropout rates of 50% or higher. The SFPE (2012) estimated that up to 70% of African American males who enter ninth grade will not graduate with their cohort. Further, educators recognize math as an area of concern for African American males, and Algebra I, primarily recognized as a ninth-grade course, is categorized as a gatekeeper course (Rech & Harrington, 2000; United States Department of Education [DOE], 2008).

Research has indicated that students who do not successfully complete Algebra I by the end of ninth grade doubtfully will complete the high school math sequence, which includes, Algebra I, Geometry, Algebra II, Trigonometry, and Calculus (Schmidt, 2003). Moreover, these students will unlikely graduate from college (DOE, 2008). In contrast, White students will probably pursue advanced mathematics classes than are African American students (Kelly,
With the lack of skills and training in mathematics, minority students are unlikely to pursue college STEM majors, as these courses require a firm foundation in mathematics (NCTM, 2000).

Research has indicated that students’ math self-efficacy (Cordero, Porter, Israel & Brown, 2010; Marra, Rodgers, Shen & Bogue, 2009; Peters, 2013), academic engagement (Cooper, Robinson, & Patall, 2006; Gill & Schlossman, 2003; Maltese, Tai, & Fan, 2012; Singh, Granville, & Dika, 2002), and student-teacher relationships (Chhuon & Wallace, 2014; Cornelius-White, 2007; Hughes, Luo, Kwok, & Loyd, 2008; Martin & Dawson, 2009) are related to academic achievement. The current study used Bandura’s (1986) social cognitive theory (SCT) as a theoretical framework to examine the influence of three key factors—individual (self-efficacy), behavioral (academic engagement), and environmental (student-teacher relationships)—on the academic achievement of ninth-grade African American male students in Algebra I.

Purpose of the Study

The purpose of this study was to determine the influence of math self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement among ninth-grade African American male students.

Statement of the Problem

African American males have the lowest achievement scores, highest high school dropout rates (Hamlet, 2012), and lowest high school graduation rates (SFPE, 2012). These students are also less likely to graduate from college (DOE, 2008). In the 2009–2010 school year, 52% of African American males in the United States graduated from high school compared to 78% of White males (SFPE, 2012). The SFPE (2012) noted, “Black males have been the least likely to
secure a high school diploma in four years after [entering] high school” (p. 6). A plausible correlation with the high school dropout rate is that more than 27% of African Americans aged 16 to 19 are unemployed (United States Bureau of Labor Statistics [BLS], 2015). These numbers are disconcerting given that African Americans make up only 13.1% of the total United States population (United States Census Bureau [USCB], 2010).

Minority students are also underrepresented in STEM-related courses in college and careers (Museus et al., 2011). Gomez (2012) suggested a relationship between this underrepresentation in STEM-related courses and careers and the high number of minority students who drop out Algebra I classes. Accordingly, these students are unlikely to complete the high school math course sequence (Schmidt, 2003). The DOE (2008) suggested that advanced math skills correlate significantly with success in college and higher earnings. Specifically, completion of Algebra II is correlated with college graduation:

Among African-American and Hispanic students with mathematics preparation at least through Algebra II, the differences in college graduation rates versus the student population in general are half as large as the differences for students who do not complete Algebra II (p. xiii).

Adding to the disparity in Algebra I completion among African American male students, is that these students are three times more likely to be suspended or expelled from school compared to their White counterparts (National Education Association [NEA], 2011). Minority students are also disproportionately identified and placed in special education programs and underrepresented in advanced academics or gifted and talented (GT) programs (Hargrove & Seay, 2011). Further, African American male adults are more likely to end up in jail compared to White males (Reddick & Heilig, 2012). According to the Page, Petteruti, Walsh, and
Ziedenberg (2007), surveys have steadily demonstrated that the imprisoned population less educated than the general population. In 2000, African American males were incarcerated at 7.7 times the rate of White males (Goode, 2013). This alarming rate of incarceration mirrors the effects of incarceration on the economy, local workforce, crime, and economic loss.

Although the educational disparity between African American and other ethnic groups has attracted much attention from educational stakeholders, researchers have made limited attempts to develop theoretical models to isolate the underlying social issues that underscore low student scores related to math achievement (Estrada-Hollenbeck, Woodcock, Hernandez, & Schultz, 2011). Moreover, limited research exists on individual, behavioral, and environmental factors that affect minority student achievement in STEM courses (Singh et al., 2002). The lack of capacious research on the effects of the three constructs on Algebra I achievement among high school male students provides the impetus for the current study. Further, minorities in the United States are expected to increase to comprise at least 33% of the population over the next 20 years (Wimberly, 2002). To this end, it is necessary to develop empirical statistical models to identify probable factors that affect low mathematics achievement among African American males.

**Significance of the Study**

Math is considered a springboard to future academic success, and it is a gateway to college, the most lucrative careers (Museus et al., 2011; NTCM, 2000), and to solving societal concerns such as global warming and space exploration. Moreover, math achievement is the foundation for success in STEM-related courses (Museus et al., 2011). Typically, higher institutions of learning categorize Algebra I as a gatekeeper course, which suggests that if a student is not successful in Algebra I, he or she will be unable to pursue certain college majors.
that require mathematics as a prerequisite (DOE, 2008; Rech & Harrington, 2000). Minorities and women are often discouraged from pursuing math because it is presumed to be difficult for these populations (Rech & Harrington, 2000). Minority student performance in mathematics, particularly in Algebra I, is a fundamental reason why disparities in STEM careers are prevalent (Rech & Harrington, 2000). Therefore, studying this population is noteworthy as stakeholders seek to determine factors that impede minority students from pursuing STEM-related courses in college and to understand why these students are underrepresented in STEM careers.

Numerous researchers have examined the association between self-efficacy (Cordero et al., 2010; Fast et al., 2010; Peters, 2013), academic engagement (Cooper et al., 2006; Gill & Schlossman, 2003; Maltese et al., 2012), student-teacher relationships (Chhuon & Wallace, 2014; Cornelius-White, 2007), and mathematics achievement from a unidimensional perspective. Therefore, a multi-faceted perspective is warranted to ascertain whether Bandura’s (1986) assumptions of SCT remain viable for ninth-grade male students and their performance in Algebra I. Specifically, the researcher addressed a gap in the literature on the interaction between individual, behavioral, and environmental constructs and Algebra I achievement among ninth-grade African American male students.

The findings of this study bridge the gap in the literature on male achievement as it is one of the few studies to scrutinize the effects of self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement of high school African American male students using a nationally representative sample. Equally significant, the current study contributes to existing knowledge using structural equation modeling (SEM) to discern the influence of the three latent variables on Algebra I achievement among high school African American male students in public schools across the United States.
Research Questions

The fundamental objective of this study was to examine self-efficacy, academic engagement, and student-teacher relationships, and to determine how these constructs influence Algebra I achievement among ninth-grade African American male students through the lens of SCT (Bandura, 1986). Based on the assumptions of SCT and the literature review, the researcher developed the following research questions:

1. Is self-efficacy related to Algebra I achievement among ninth-grade African American male students across the United States?

2. Is academic engagement related to Algebra I achievement among ninth-grade African American male students across the United States?

3. Are student-teacher relationships related to Algebra I achievement among ninth-grade African American male students across the United States?

Theoretical Framework

This study is grounded in SCT, which postulates that human functioning, learning, and performance are a triad of complex interactions between personal (cognitive-affective), behavioral, and environmental determinants (Bandura, 1977, 1986). Social cognitive theory emanated from Bandura’s research on self-regulation and self-efficacy in the 1980s. Bandura encapsulated the triad perspective as, “What people think, believe, and feel affects how they behave. The natural and extrinsic effects of their actions, in turn, partly determine their thought patterns and affective reactions” (p. 25).

The individual dimension of SCT emphasizes self-efficacy (Bandura, 1986, 1991, 2005). Self-efficacy is vital because “the types of outcomes people anticipate depend largely on their judgments of how well they will be able to perform in given situations” (Bandura, 1986, p. 392).
Equally, self-efficacy is instrumental to exercising control over an individual’s functions and the events that affect his or her life (Bandura, 2005). Bandura (1991, 2005) upheld that people’s beliefs about their potential to regulate the choices they make, their ambitions, how hard they work toward a goal, and how much pressure they can tolerate in challenging situations. Further, self-efficacy influences the amount of stress one can withstand in demanding environments.

The behavior dimension of SCT postulates that people have to believe that they have the power to affect change by their actions (Bandura, 2005). Bandura’s seminal quasi-experimental studies established that behavior is influenced by social beliefs and outcome expectations rather than by infused reinforcements (Bandura, 1991). Additionally, one hypothesis of SCT is that the interplay of individual, behavioral, and environmental factors determines one’s actions (Bandura, 1991).

As for the environmental dimension of SCT, Bandura (2004) believed that people have to be given the necessary resources and environmental supports to realize their desires fully. Bandura maintained, “A person’s success depends on the nature and modifiability of the environment” (Bandura, 2005, p. 18). Bandura also stated that the environment is not unidirectional, rather it takes three forms: imposed, selected, and created. Generally, people do not have a choice on their imposed environments; nonetheless, the outcomes of imposed environments depend on the choices people make (Bandura, 2005).

Summary

Research suggests that African American males have the lowest scores on Algebra I standardized assessments and high school dropout rates of 50% or more (Hamlet, 2012), and they lag behind in graduation rates (SFPE, 2012). According to the National Center for Education Statistics [NCES] (2011), 36% of African American students scored in the bottom...
quintile of Algebra I tests compared to 14.1% of White students. Furthermore, the SFPE (2012) extrapolated that up to 70% of African American males who entered ninth grade would not graduate high school with their cohorts.

Prior studies have examined the association between self-efficacy (Cordero et al., 2010; Fast et al., 2010; Peters, 2013), academic engagement (Cooper et al., 2006; Gill & Schlossman, 2003; Maltese et al., 2012), student-teacher relationships (Chhuon & Wallace, 2014; Cornelius-White, 2007), and math achievement; however, such research has not been conducted at a national level. Further, a number of studies evaluated the relationship between the three constructs and math achievement from a unidimensional approach. The current study used a multi-faceted approach with a focus on Algebra I among ninth-grade African American males from a national perspective. Algebra I was chosen because this course is considered the gatekeeper to math advanced course placement (DOE, 2008; Rech & Harrington, 2000) and to prospective STEM career advancement (Museus et al., 2011).

This study focused on the effects of self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement of ninth-grade African American male students. Based on Bandura’s (1986) SCT, the researcher hypothesized that self-efficacy, academic engagement, and student-teacher relationships would affect Algebra I achievement among ninth-grade African American male students. Structural equation modeling was used to explore the influence of these constructs on Algebra I achievement.
CHAPTER 2
LITERATURE REVIEW

Multiple factors, including teacher and school environment, affect math achievement among male students (Petty, Harbaugh, & Wang, 2013; Stewart, 2006). Additional factors include the amount of time students spend doing their homework (Flowers & Flowers, 2008), parental expectations of their children’s educational success (Stewart, 2006), parental involvement, school factors, students’ socioeconomic status (SES) (Petty et al., 2013; Stewart, 2008), student aspirations (Lynn, Bacon, Totten, Bridges, & Jennings, 2010), and teacher expectations (National Council of Teachers of Mathematics [NCTM], 2000; Weinstein, 2002).

This chapter includes a synthesis of previous research that has examined self-efficacy, academic engagement, student-teacher relationships, and their influence on student academic achievement.

Self-Efficacy and Academic Achievement

Self-efficacy refers to beliefs about one’s potential to learn or perform at specific levels (Bandura 1977, 1986). Usher and Pajares (2008) noted,

Self-efficacy beliefs help determine the choices people make, the effort they put forth, the persistence and perseverance they display in the face of difficulties, and the degree of anxiety or serenity they experience as they engage in myriad tasks that comprise their life. (p. 751)

Several factors contribute to an individual’s self-efficacy, including, prior performance, accomplishments, one’s biological and emotional compositions, social learning, societal expectations (Bandura, 1986), family background, peers, and school environment (Schunk & Pajares, 2002). Of these factors, prior success with similar tasks exerts paramount influence on
self-efficacy (Bandura, 1986). Self-efficacy is also related to three motivational constructs: outcome expectations, self-concept, and perceived control (Schunk & Pajares, 2002).

Outcome expectations are “the consequences expected from one’s … actions are related to self-efficacy beliefs but they are not synonymous” (Schunk & Pajares, 2002, p. 3). For example, a student with high self-efficacy may believe he or she has the potential to learn mathematics. Despite this potential, the student may expect to get a low grade in mathematics if he or she feels that the instructor does not care about him or her.

Self-control beliefs denote self-perceptions developed from experiences with and an understanding of the environment. These beliefs are manipulated by reinforcements and evaluations from significant others, including peers (Schunk & Pajares, 2002). Although self-control and self-efficacy are related, they do not measure the same trait. Self-efficacy is principally concerned with judgments about one’s potential, while self-control embraces the feelings of self-confidence that accompany capability beliefs (Schunk & Pajares, 2002). Finally, perceived control refers to the belief that people can have authority over what they can learn and how they perform. Those who have perceived control believe they can initiate and sustain behaviors geared toward learning and performing compared to those who have a low sense of control over their potential (Schunk & Pajares, 2002).

According to Zimmerman (2000), students’ beliefs about their academic potential play a pivotal role in their desires to achieve. Self-efficacy measures emphasize performance potential rather than student qualities, such as physical and psychological characteristics. Self-efficacy beliefs are multi-dimensional and function differently in different circumstances (Zimmerman, 2000). For example, efficacy beliefs about performing math tasks may be different from beliefs about a science examination. Furthermore, environment can influence one’s efficacy for a
particular task. For example, someone taking an examination in a noisy hall might not be able to concentrate on the task. Zimmerman (2000) noted that self-efficacy judgments point to prospective functioning; accordingly, they are assessed before the student performs a relevant task.

Bandura (1977) contended that perceived self-efficacy influences the activities and settings one chooses to pursue. Additionally, efficacy expectations determine the amount of effort people exert and how they persist when they encounter obstacles and objectionable experiences. Bandura believed that students with high self-efficacy beliefs willingly participate in different social and academic activities, are hard workers, are persistent, and seldom react emotionally when confronted with situations that challenge their potential. Efficacious students are often ready for challenges, and they take on demanding tasks compared to inefficacious students (Zimmerman, 2000). Zimmerman (2000) upheld, “Self-efficacy beliefs also provide students with a sense of urgency to motivate their learning through use of self-regulatory processes such as goal setting, self-monitoring, self-evaluation, and strategy use” (p. 87).

Research suggests that self-efficacy is a viable predictor of future performance given past behaviors (Bandura, 1977). Findings from meta-analyses indicated that “efficacy beliefs contribute significantly to the level of motivation and performance” (Bandura & Locke, 2003, p. 87). Similarly, a correlation exists between self-efficacy beliefs and specific domains, which can predict an outcome when one is familiar with a task (Bandura, 1986). Pajares and Miller’s (1994) path analysis study examined self-efficacy and self-concepts beliefs in mathematical problem solving to confirm Bandura’s (1986) hypotheses on the predictive and mediational roles of self-efficacy beliefs in math. The authors found that math self-efficacy was a better predictor
of math problem solving than of math self-concepts, perceived utility of math, prior math experience, or gender (Pajares & Miller, 1994).

Peters (2013) investigated the association between classroom climate, self-efficacy, and mathematics achievement among undergraduate students. She administered the Mathematics Self-Efficacy Scale-Revised and final Algebra I examinations to 326 students. Her multi-level analysis revealed that students with higher mathematics self-efficacy had higher achievement on the Algebra I assessments. Although most male respondents reported higher mathematical efficacy than did female students, Peters found no significant gender differences in math achievement.

Cordero et al. (2010) conducted a comparison study to determine whether interventions to increase math self-efficacy enhanced college undergraduates’ math self-efficacy. They randomly assigned 51 freshmen students to the experimental group (performance accomplishment plus belief perseverance) and 48 students to the control group (performance accomplishment only). An analysis of covariance (ANCOVA) revealed that the experimental group exhibited notably higher math self-efficacy than the control group, $F(1, 95) = 8.82, p < .05$, partial $\eta^2 = .09$. Cordero et al. concluded that self-persuasion activities might significantly enhance math self-efficacy.

Cordero et al. (2010) also conducted independent $t$-tests to examine gender differences among participants’ scores on the math test, ratings of their performance on the math test, and math efficacy. The analysis revealed no statistically significant gender differences in math test scores. Nonetheless, a statistically significant difference did exist between male and female participants’ math self-efficacies. Precisely, female participants reported significantly less math
self-efficacy ($M = 6.77, SD = 1.30$) than did male participants ($M = 7.43, SD = 1.04$; $t(97) = -2.733, p < .017$).

Fast et al. (2010) aimed to determine whether math self-efficacy mediated the effect of perceived classroom environment on student performance on a standardized math test. Over 1,100 middle school students completed four items of the Student Motivation Questionnaire (SMQ) that were adapted from existing scales of math self-efficacy. Students’ responses to the SMQ questionnaire were merged with their 2005–2006 and 2006–2007 academic year math scores on the California Standards Test (CST). A multi-level analysis revealed that students who perceived their classroom environments as more caring, challenging, and mastery focused had statistically significantly higher levels of math self-efficacy, $t(1,071) = 5.27, p < .001$, which positively predicted math performance. Additionally, variables that indirectly affected classroom environment had small but statistically significant mediating effects on self-efficacy (Fast et al., 2010).

Marra et al. (2009) aimed to understand constructs related to the success of minorities, especially women, studying engineering. Using the Longitudinal Assessment of Engineering Self-Efficacy (LAES), they collected data from five colleges during the 2003 and 2004 fall semesters. They sought to determine whether differences existed in self-efficacy scales and whether the differences varied from year to year. Their analysis produced mixed results. Overall, respondents’ feelings of efficacy increased; however, African American students demonstrated a significant decrease in the inclusion feeling scale from 2003 to 2004 compared to other demographic groups. African American students’ low inclusion scores raised concerns that they were more likely to drop out of the engineering program. To this end, Marra et al. wrote, “A strong sense of self-efficacy, especially for women students who are underrepresented in
engineering classrooms, can help them persist and enable them to become practicing engineers” (p. 35).

Academic Engagement and Academic Achievement

Numerous researchers have investigated academic engagement with respect to behaviors, attitudes, feelings (Johnson, Crosnoe, & Elder, 2001; Whitton & Moseley, 2014), commitment, enthrallment, sense of belonging, and being a part of something (Whitton & Moseley, 2014). Johnson et al. (2001) suggested that a clear distinction should exist between affective and behavioral dimensions of academic engagement. Research on the relationship between the amount of time spent on homework and student outcomes is mixed.

Some researchers have demonstrated that more time investment in completing homework during non-school hours is positively related to higher student achievement in mathematics (Cooper et al., 2006; Maltese et al., 2012; Strayhorn, 2010). Others have established that the amount of time spent on homework is inversely related to math achievement (Maltese et al., 2012; Trautwein, 2007). Although the findings regarding the number of hours spent on homework and achievement are mixed, Trautwein (2007) found that the effort students put into completing homework positively predicted math achievement.

The issue of homework is contentious in the United States as proponents of homework contend that more is beneficial and that time spent on homework is an indicator of students investing time and effort into their studies (Gill & Schlossman, 2003). On the other hand, findings suggest that time spent on homework is inversely related to student achievement and that lengthy homework does not motivate students to devote more time to their studies (Maltese et al., 2012; Trautwein, 2007). Furthermore, time devoted to homework completion is inversely related to achievement gains (Trautwein, 2007).
Maltese et al. (2012) examined the effects of homework completion on high school student outcomes in science and mathematics. Using the National Education Longitudinal Study (NELS) of 1990 and the Education Longitudinal Study (ELS) of 2002, they aimed to determine the association between the amount of time spent on homework and academic achievement as measured by students’ grades on 10th-grade science and math standardized assessments. Cross-tabulations revealed that students who spent 1 to 2 hours completing homework daily earned the best grades and realized the highest test scores on standardized assessments. Conversely, the multiple regression analyses suggested that time spent on homework was not statistically significantly related to final grades, and no considerable difference were found in grades between students who completed homework and those who did not.

In contrast, Maltese et al. (2012) found a significant positive relationship between time spent on homework and achievement on standardized test scores. These findings indicated that students who completed any amount of homework earned higher test scores compared to their peers who did not complete homework. Maltese et al. extrapolated the regression analyses to SAT math achievement and found that students who spent 31 to 90 minutes in a typical day on homework scored, on average, 40 points higher on the SAT math subtest compared to those who did not devote any time to homework. Maltese et al. concluded that a possible explanation for the increased SAT math subset scores was that students who completed their homework had more opportunities to practice similar items as those on the standardized assessments.

Cooper et al. (2006) conducted a meta-analysis of the effects of homework on student achievement. They reviewed studies that had established a causal link between homework and student outcomes using four research designs: (a) randomized assignment of classes or students to homework and non-homework groups, (b) non-randomized group assignments, (c)
multivariate analyses using secondary data, and (d) structural equation modeling (SEM) analyses using primary data. The $d$-index mean unit tests score, which revealed differences between students who diligently completed homework and those who did not, ranged from $d = .39$ to $d = .97$. The meta-analysis yielded a mean $d$-index of .60. Additionally, findings from most multivariate and SEM analyses revealed positive and statistically significant regression coefficients across all subject areas. Overall, most randomized studies had design flaws that jeopardized the ability to establish casual inference. However, findings from the non-randomized study designs yielded positive relationships between homework and achievement that withstood scrutiny.

Bempechat, Li, Neier, Gillis, and Holloway (2011) conducted a qualitative study to examine the perceptions of homework among diverse low-socioeconomic (SES) ninth graders who attended low-performing schools. The authors found that high- and low-achieving students attached different meaning to homework. For example, high-achieving students found homework boring when they did not learn much from the assignments. Similarly, low-achieving students perceived homework as too much or as uninteresting. Bempechat et al. also found that high-achieving students diligently completed homework assignments although they did not learn much or felt it was boring, thus, they exhibited academic engagement. In contrast, low-achieving students tried to avoid homework and did not comply with the demands of the assignments; hence, they exhibited disengagement. In addition to interviewing students, Bempechat et al. examined student grade point average (GPA) and found that high-achieving students maintained higher GPAs, which indicates that grades are a measure of motivation.

Trautwein (2007) conducted three studies to evaluate the prevailing claim that the amount of time devoted to homework is related to student achievement and achievement gains.
Trautwein compared and contrasted the amount of time spent on homework and other covariates. More concretely, he examined homework frequency and the amount of effort students put into homework. His findings suggested that homework assignments had a positive class-level effect on achievement and that completing homework had a school-level effect on achievement gains. However, the amount of time students devoted to homework did not predict achievement or achievement gains.

Flowers and Flowers (2008) analyzed the NELS-1988 to determine factors that affected reading achievement among urban African American high school students. They used least square regression statistical methods whereby they regressed the amount of time students spent doing homework, family income, and parents’ expectations of future educational attainment against reading scores. Their findings suggested that all the three independent variables statistically influenced reading achievement of African American students in urban high school settings, with time spent on homework exhibiting the largest standardized beta coefficient.

Singh et al. (2002) examined the NELS-1988 data using structural equation modeling to ascertain whether the amount of time students spent on homework, students’ motivation and interest were related to math and science achievement among eighth graders. These authors’ findings revealed that the amount of time student devoted to homework had the strongest effect on math and science academic performance. Similarly, Strayhorn’s (2010) three-level hierarchical linear model analysis found that students who spent more time on their homework had higher math scores.

Student-Teacher Relationships and Academic Achievement

A considerable body of research has shown that students’ affective relationships with their teachers influence academic and developmental outcomes (Chhuon & Wallace, 2014;
Cornelius-White, 2007; Hughes et al., 2008; Martin & Dawson, 2009). Relationship in this study refers to the way in which two or more people or groups talk to, behave toward, and deal with each other. The majority of theoretical perspectives on student-teacher relationships postulate that students’ lack of relationships with their teachers prompt insecure feelings and distress and consequently limit students’ abilities to concentrate on academic and social learning activities (Spilt, Wu, Hughes, & Kwok, 2012). Simply put, teachers who establish and maintain relationships with their students respond differently to students’ individual needs (Chhuon & Wallace, 2014). Likewise, students who believe they have good relationships with their teachers are likely to exert more effort on their studies and to learn more from their teachers because they respect and trust their teachers (Noddings, 1992). Student-teacher relationships foster student engagement in learning activities and are pivotal to academic achievement (Hughes et al., 2008).

Chhuon and Wallace (2014) conducted a focus group with high school students to explore adolescents’ opinions and experiences of what “being known” in school meant to them. The findings suggested that being known by a teacher meant that the students were connected to the school. Three major themes emerged from the qualitative study: (a) students expressed a desire for their teachers to move beyond just teaching and assigning them work to knowing and establishing relationships with them, (b) students felt that their teachers did not provide them instrumental support to master academic skills, and (c) teachers were generally inattentive and did not care about their students. To this end, Chhuon and Wallace argued that as adolescents navigate their senses of increased freedom and opportunities to make decisions on their own, they need guidance and feelings of being connected to their school environments. Chhuon and Wallace concluded that student-teacher relationships help students develop positive identities.
and aspirations and that these relationships were the most significant school-based relationships that students could develop.

Martin and Dawson (2009) pointed out that relationships are fundamental pillars of student motivation, engagement, and achievement. Teachers who establish and maintain relationships with their students are likely to promote interested, engaged, and higher achieving students. Martin and Dawson reviewed the effect of interpersonal relationships on motivation and achievement. They concluded that meaningful relationships with teachers were pivotal to adolescents’ capacities to function effectively socially and academically. They also concluded that high quality interpersonal relationships contributed to students’ academic motivation, engagement, and achievement.

Friends, teachers, and parents are vital sources of students’ social support. Rosenfeld, Richman, and Bowen (2000) compared school outcomes of students who had different perceptions on the support they received from their parents, friends, and teachers. Specifically, they investigated how a representative national sample of middle and high school students who received low and high support from parents, teachers, and students differed in their behaviors, school affects, and achievement. Rosenfeld et al. (2000) found that teachers played a vital role in social support and school outcome relationships. Moreover, students who reported receiving low support from teachers, parents, and peers had the lowest school outcomes. In contrast, students who received high support from one or two sources of support had better attendance, spent more hours studying, had fewer behavioral issues, were more engaged, and earned better grades. Similarly, Wissink et al. (2014) found that teacher-student relationships were associated with less student misconduct in school and less delinquency and vandalism outside of school.
Researchers have established a positive link between student-teacher relationships and completion of the General Educational Development (GED) program. Reio, Marcus, and Sanders-Reio (2009) explored how student-teacher relationships and attachment styles affected students’ completion of the GED program. Their findings suggested that student-teacher relationships were positively related to earning a GED. Additionally, a logistic hierarchical regression analyses accounted for 70.9% of variance after controlling for demographic variables. As a result, positive peer-to-peer friendships and student-teacher relationships yielded positive influences on school completion. Conversely, students who exhibited poor relationships with their instructors did not complete their GED programs. Reio et al. noted, “Forming positive relationships with other students and instructors contributes to school completion” (p. 67).

Ellerbrock, Kiefer, and Alley (2014) conducted a qualitative study in which they interviewed 18 middle school students, five teachers, and one administrator. The findings revealed that student-teacher relationships promoted middle school students’ sense of school belonging. Specifically, teachers who established relationships with their students maintained caring connections and were more responsive to their students’ needs; therefore, they endorsed the students’ sense of belonging. The findings also indicated that student-teacher relationships are fundamental to meeting students’ needs and promoting school connectedness at the middle school level.

McHugh, Horner, Colditz, and Wallace (2013) investigated students’ perceptions of the bridges that promote and the barriers that hamper positive student-teacher relationships. Findings from a focus group suggested that to foster student-teacher relationships, teachers must make an effort to engage or connect with students as doing so shows students that the teachers care about their well-being and success as individuals. Teachers who stereotype students and do
not pay them attention demonstrate that they do not care about and are not interested in their academic success. McHugh et al. (2013) also found that teachers and students working together to establish appropriate behavior guidelines within their normative roles directly translates into academic achievement and positive youth outcomes.

Cornelius-White (2007) conducted a meta-analysis to explore the effects of learner-centered student-teacher relationships on student achievement. He synthesized 119 studies conducted from 1948 to 2004 with 1,450 findings based on data from 355,325 students, 14,851 teachers, and 2,339 schools. The findings revealed an average correlation of $r = 0.34$ ($SD = .20$) between learner-centered relationship variables and combined student outcomes and a mean correlation of 0.31 ($SD = .28$) between positive student-teacher relationships and positive student outcomes. Cornelius-White concluded that learner-centered student-teacher relationships are positively related to student outcomes.

Decker, Dona, and Christenson (2007) conducted an exploratory study to investigate the relationship between student-teacher relationships and outcomes for behaviorally at-risk African American students who were slated for referral to special education. They used multi-rater and mixed method research practices to collect data from students and teachers. Students responded to questionnaires that addressed their perspectives on their relationships with their teachers, their engagement in learning, and their social skills. The teachers completed questionnaires that addressed their perspectives on their relationships with students and student engagement in learning, social skills, academic outcomes, and disciplinary infractions.

Decker et al. (2007) analyzed the data using a series of hierarchical multiple regression analyses at the student and teacher levels to predict at-risk African American students’ academic, social, engagement, and behavioral outcomes. The findings suggested that students desired to be
closer to their teachers and perceived their relationships with their teachers positively. In contrast, teachers perceived relationships with their students negatively. These authors noted, “Perhaps the ways in which students interacted with their teachers led teachers to feel negatively about the students” (p. 102). The findings suggest that student-teacher relationships were more significant predictors of social-emotional and engagement outcomes than of academic outcomes, irrespective of the data source (i.e., student or teacher). Decker et al. concluded that student-teacher relationships predict student engagement among at-risk African American students.

Prior research suggests that African American students are more likely to experience negative relationships from their teachers than from their peers (Saft & Pianta, 2001). To this end, Murray and Zvoch (2011) examined student-teacher relationships among low SES, high-risk middle school African Americans with and without behavioral problems to ascertain differences and similarities in self-reported student and teacher data on student-teacher relationships. They collected data on emotional, behavioral, and school-related adjustment outcomes from both teachers’ and students’ perspectives.

Students with behavioral problems reported lower trust in their relationships with their teachers than did students without behavioral problems. Teachers perceived their relationships with students with behavioral problems as lower in closeness and filled more with conflict compared to their relationships with students without behavioral problems (Murray & Zvoch, 2011). Moreover, Murray and Zvoch (2011) found that the quality of student-teacher relationship was related to students’ emotional, behavioral, and school-related adjustments. They concluded that irrespective of holding race and SES constant, students with behavioral problems “are at greater risk of experiencing poorer quality relationships with teachers than similarly matched students without behavioral problems” (Murray & Zvoch, 2011, p. 50).
Konishi, Hymel, Zumbo, and Li (2010) explored the relationship between student-teacher relationships, school bullying, and academic performance using the Programme for International Student Assessment (PISA) data collected from 15-year-old students in 10 Canadian provinces. Findings of the multi-level analyses established that student-teacher relationships were related positively and significantly to math achievement. Additionally, students who viewed their relationships with their teachers as positive attained higher math scores than were students who perceived their relationships with teachers as negative. Student-teacher relationships accounted for 81% variance in students’ math achievement. Konishi et al. conducted separate analyses for boys and girls and found that math achievement was positively related to meaningful student-teacher relationships irrespective of gender. These findings suggested that interpersonal relationships at school positively affect student achievement.

Roorda, Koomen, Spilt, and Oort (2011) conducted a meta-analysis to determine the relationship between affective student-teacher relationship qualities and student engagement and achievement. They reviewed 99 studies that included Pre-K to 12th grade; they conducted four separate analyses of relationships between (1) positive student-teacher relationships and student engagement, (2) negative student-teacher relationships and student engagement, (3) positive student-teacher relationships and academic achievement, and (4) negative student-teacher relationships and student achievement. The analyses yielded positive statistically significant relationships between the independent and dependent variables. Additionally, the analyses yielded a moderate effect ($r = 0.39, p < .01$) between positive relationships and student engagement, and a small effect between student-teacher relationships and student achievement. In contrast, Roorda et al. found that negative student-teacher relationships were inversely related to both student engagement and academic achievement ($r = -0.31, p < .01$ and $r = -0.15, p < .01$).
Researchers have suggested that boys are unlikely to establish meaningful relationships with their teachers. Murray and Zvoch (2011) examined at-risk African American students and the relationships they established with their teachers. They found that male students with behavioral problems had the poorest relationships with their teachers. Accordingly, these students experienced difficulty adjusting emotionally and behaviorally to school.

Research on student-teacher relationships and student age is contentious. Some researchers have suggested that younger children are influenced more so by meaningful relationships with teachers, while others have contended that student-teacher relationships affect older children. For example, Roorda, et al. (2011) found that student-teacher relationships were pivotal for academic adjustment of older students. In contrast, Rosenfeld et al. (2000) suggested that teachers play a vital role in the social support-school outcome relationship among middle and high school students.

Summary

Research has indicated that students’ beliefs about their potential to succeed plays a pivotal role in their desires to achieve (Zimmerman, 2000). Correspondingly, Bandura (1997) noted that self-efficacy influences the activities and settings one chooses to pursue. For example, an efficacious person in math is likely to pursue advanced math classes, is willing to face challenges, and is willing to tackle demanding tasks (Zimmerman, 2000). Further, self-efficacy is related to high student outcomes (Cordero et al., 2010; Peters, 2013).

Studies on academic engagement and student outcomes have yielded mixed results. While some findings suggest that the amount of hours spent on homework is related to higher student outcomes (Bempechat et al., 2011; Cooper et al., 2006; Maltese et al., 2012), three studies conducted by Trautwein (2007) negated these findings. Specifically, Trautwein found
that time devoted to homework completion was inversely related to achievement and achievement gains.

Finally, a considerable body of research has shown that students’ affective relationships with their teachers influence their academic and developmental outcomes (Chhuon & Wallace, 2014; Cornelius-White, 2007; Hughes et al., 2008; Martin & Dawson, 2009). Student-teacher relationships are fundamental pillars of student motivation, engagement, and achievement (Martin & Dawson, 2009). Considering the extant research, self-efficacy, academic engagement, and student-teacher relationships are valuable points of research in examining academic success among ninth-grade African American male students in Algebra I.
CHAPTER 3
METHODS

The purpose of this study was to examine the effects of personal, behavioral, and environmental factors on Algebra I achievement among ninth-grade African American male students. Specifically, the researcher examined the relationship between self-efficacy, academic engagement, and student-teacher relationships and Algebra I achievement among ninth-grade African American male students using Bandura’s (1986) social cognitive theory (SCT) as the theoretical framework and structural equation modeling (SEM) as the statistical analysis technique. This chapter includes a description of the research methods used to conduct the study, the hypothesized theoretical model, research design, study participants, variables examined and their operational definitions, and the data analytic techniques.

Hypothesized Theoretical Model

Figure 3.1 illustrates the conceptual model of the effects of self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement, and highlights the hypothesized relationships evaluated in the current study. The solid lines in the model show the theoretically assumed direct effects examined and the dashed lines represent the hypothesized indirect effects.

Based on the assumptions of SCT and the literature review, the researcher hypothesized that math self-efficacy, academic engagement, and student-teacher relationships would affect participants’ Algebra I achievement. More concretely, the researcher expected that self-efficacy would be positively related to performance in Algebra I among ninth-grade African American males. The positive effect was expected because prior research has found a statistically
significant relationship between math self-efficacy and math achievement (Bandura, 1977; 1986; Fast et al., 2010; Peters, 2013; Zimmerman, 2000).

The researcher also hypothesized that higher academic engagement, as measured by the amount of time students devoted to completing math and additional homework assignments, would be associated with learning and acquiring academic skills, which would lead to higher math achievement. Previous research supports this hypothesis, as findings have demonstrated that the amount of time students devote to homework influence student outcomes (Cooper et al., 2006; Flowers & Flowers, 2008; Maltese et al., 2012; Strayhorn, 2010).

Research has also indicated that students’ affective relationships with their teachers influence academic and developmental outcomes (Chhuon & Wallace, 2014; Cornelius-White, 2007; Hughes et al., 2008; Martin & Dawson, 2009). Consequently, the researcher hypothesized that student-teacher relationships would directly affect Algebra I performance.
Research Design

The researcher used a national data set to apply a causal-comparative research design and SEM to investigate the hypothesized relationships between the latent variables of self-efficacy, academic engagement, student-teacher relationships and their effects on Algebra I achievement. According to Isaac and Michael (1995), causal-comparative research design explores possible cause-and-effect relationships by examining existing phenomenon and searching through the data for plausible causal factors. Causal-comparative research also allows the researcher to study cause-and-effect relationships where experimental manipulation is not possible (Gall, Gall, & Borg, 2003). Although causal comparative research designs can be used to study cause-and-effect relationships, they cannot be used to establish causality (Gall et al., 2003).

Data and Study Participants

Data used for the current study were collected from the National Center of Education Statistics (NCES) High School Longitudinal Study of 2009 (HSLS:09), a nationally representative study of more than 23,000 ninth graders in 944 public, private, and Catholic schools (Ingels et al., 2011). Data were collected from students, parents, math and science teachers, school administrators, and school counselors. Participants of the HSLS:09 were sampled using a 2-stage process. Initially, stratified random sampling among schools was used to identify 1,889 eligible schools. Of the 1,889 eligible schools, 944 schools participated in the study, which yielded a 55.5% (weighted) or 50% unweighted response rate (Ingels et al., 2011). Students were randomly sampled from the eligible schools in the second sampling stage. The target population was defined as all ninth-grade students who attended study-eligible public, private, and Catholic schools across the United States in the 2009 fall term (Ingels et al., 2011). For the current study, the researcher evaluated only responses to the student questionnaire from
ninth-grade African American male students who were enrolled in public schools across the United States (see Appendix A).

The HSLS:09 study followed participants throughout their secondary and postsecondary years. The study also focused on students’ decisions related to the courses and occupations they intended to pursue and the reasons for these pursuits. Of special focus of the HSLS:09 were science, technology, engineering, and mathematics (STEM)-related pursuits (Ingels et al., 2011). The first wave of data collection (base year 2009) occurred in the fall of participants’ ninth-grade year. Given the topic of the present study, the current sample was limited to African American male students during this timeframe. The representative national sample comprised of 933 African American male students enrolled in public schools across the United States. Of the 933 respondents, 231 participants with 15% or more missing data and five cases identified as potential outliers were deleted, which resulted in the final nationally representative analytical sample of 697 male student participants. Sampling weights yielded a target population of 180,711 African American males who were enrolled in the ninth grade during fall 2009 in public schools across the United States.

Overview of Constructs Examined

Fundamentally, the researcher aimed to determine the relationships between Algebra I achievement and three latent variables among ninth-grade African American male students. Social cognitive theory hypothesizes that human learning is an interrelationship between individual, behavioral, and environmental factors (Bandura, 1977, 1986, 2005). Therefore, the dependent variable was students’ average composite standardized theta scores on an Algebra I test administered in the fall 2009. The Algebra I test assessed students’ algebraic skills, reasoning, and problem solving (Ingels et al., 2011). These scores were based on Item Response
Theory (IRT) scaled scores. The IRT model examines the response patterns of all students to obtain ability scores that are comparable across varying difficulty levels and test forms (Hambleton & Swaminathan, 1985).

Based on the assumptions of SCT and the findings of the literature review, the researcher hypothesized that variation in Algebra I achievement among ninth-grade male students could be explained by examining the following three latent constructs: individual (self-efficacy), behavioral (academic engagement), and environmental (student-teacher relationships). Math self-efficacy was measured as a latent variable derived from students’ responses to four items on Section C of the student questionnaire. These items evaluated students’ beliefs and confidence in understanding math assignments and textbooks and in passing math tests. Participants rated these items on a 4-point Likert-type scale (1 = *strong agree*, 2 = *agree*, 3 = *disagree*, and 4 = *strongly disagree*). Items were reverse-coded.

Academic engagement was measured as a latent variable derived from students’ responses to three items on Section E of the student questionnaire. These items aimed to determine the number of hours students spent doing math and science homework and studying for other courses. The questions had six possible responses ranging from 1 to 6 (1 = *less than 1 hour*, 2 = *1 to 2 hours*, 3 = *2 to 3 hours*, 4 = *3 to 4 hours*, 5 = *4 to 5 hours*, and 6 = *5 or more hours*). As measured, engagement elicited the number of hours students spent studying outside of the classroom. The more time students devoted to homework and studying outside of school in a typical day, the higher their academic engagement. In contrast, less time spent on homework and studying outside of school in a typical day implied academic disengagement.

Student-teacher relationship was measured as a latent variable derived from students’ responses to five student-math teacher experience items on Section C of the student
questionnaire. The questions aimed to determine whether teachers treated students with respect, teachers treated every student fairly, teachers valued or listened to students’ ideas, teachers thought that all students could be successful, and teachers thought that mistakes were okay if students learned from them. Study participants rated these items on a 4-point Likert-type scale (1 = strong agree, 2 = agree, 3 = disagree, and 4 = strongly disagree). Items were reverse-coded.

The researcher selected 12 items that seemed logically related to the study constructs and subjected them to exploratory factor analysis (EFA) to identify the underlying factor structure. Table 3.1 provides a list of the study items and the corresponding latent constructs. The questionnaire items selected for this study aimed to determine participants’ degrees of confidence; hence, items were measured using an ordinal scale. Researchers have recommended using polychoric correlation and asymptotic covariance matrices with ordinal scaled items and non-normal data, respectively (Brown, 2006; Forero, Mayden-Olivares, & Gallardo-Pujol, 2009; Kline, 2011; Nye & Drasgow, 2011; Schumacker & Lomax, 2004). Accordingly, the researcher generated polychoric and asymptotic covariance matrices in LInear Structural RELations (LISREL; version 9.2 student edition) for the confirmatory factor analysis (CFA) and SEM.
Table 3.1

*Questionnaire Items and Latent Variables*

| Item | Wording or Description and Coding | Latent Variable |
|------|-----------------------------------|-----------------
| S1C08A (S1MTESTS) | Confident 9th graders can do well on the fall 2009 math tests | Efficacy |
| S1C08B (S1MTEXTBOOK) | Certain 9th graders can understand the fall 2009 math textbook |  |
| S1C08C (S1MSKILLS) | Certain 9th graders can master skills in the fall 2009 math course |  |
| S1C08C (S1MASSEXCL) | Confident 9th graders can do well on the fall 2009 math assignments |  |
| S1E15A (S1HRMHOMEWK) | Hours spent on math homework/studying during a typical school day | Academic engagement |
| S1E15C (S1HROTHHOMWK) | Hours spent on other homework/studying during a typical school day |  |
| S1E15C (S1HROTHHOMWK) | Hours spent on science homework/studying during a typical school day |  |
| S1 C11B (S1MTCHRESPCT) | 9th grade math teachers in fall 2009 treat students with respect | Student-teacher relationships |
| S1 C11C (S1MTCHFAIR) | 9th grade math teachers in fall 2009 treat every student fairly |  |
| S1 C11A (S1MTCHVALUES) | 9th grade math teachers in fall 2009 value/listen to students’ ideas |  |
| S1 C11D (S1MTCHCONF) | 9th grade math teachers in fall 2009 think all students can be successful |  |
| S1 C11E (S1MTCHMISTKE) | 9th grade math teachers in fall 2009 think mistakes of okay if students learn |  |
| X1TXMTSCOR | Mathematics standardized theta scores | Algebra I scores |
| W1STUDENT | Base year student weight analytical scores | Weight score |

**Data Analytic Techniques**

The findings of this study advance the literature on the effects of individual, behavioral, and environmental constructs on Algebra I achievement among ninth-grade African American male students across the United States using SEM. Considerable research has been conducted on the three constructs using multivariate analytical techniques, such as multiple regression, path...
analyses, and multi-level modeling. Structural equation modeling is a powerful statistical technique that allows researchers to evaluate relationships between latent and observed variables (Kline, 2011). Additionally, SEM uses various models to identify relationships among observed and unobserved variables to provide a quantitative test of a hypothesized theoretical model (Schumacker & Lomax, 2004). Structural equation modeling is also a unique statistical technique in that it (a) estimates multiple and interrelated dependent relationships and (b) can represent latent variables in hypothesized relationships and account for measurement error (Hair, Black, Babin, Anderson, & Tatham, 2006).

The SEM data analysis technique entails two phases, the measurement and the structural phases. The measurement phase uses CFA to determine the relationship between the latent constructs and their manifested indicators. The structural phase allows the researcher to specify and test relationships between latent and dependent variables (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Blunch, 2013; Brown, 2006; Kline, 2011).

Data analytical techniques for the current study consisted of a 5-stage process: (a) evaluation of statistical assumptions, (b) EFA, (c) CFA, (d) evaluation of reliability and validity of latent constructs, and (e) SEM. Assessing the SEM statistical assumptions helped the researcher determine whether the data were suitable for CFA and SEM analyses. The researcher used EFA to identify the underlying structure of the latent constructs. The CFA was used to evaluate whether the conceptual model was a good fit and to ascertain the psychometric properties, reliability, and validity of the scales. The SEM was used to determine model fit and to ascertain the influence of the latent variables on the dependent variable.
Data Preparation and Screening

Kline (2011) recommended screening data for missing data, outliers, multivariate normality, collinearity, homoscedasticity, and sample size adequacy before subjecting the data to CFA and SEM analyses. Data preparation and screening preceding an SEM analysis are vital procedures for two reasons: (a) SEM estimation methods presume data distribution and violation of these assumptions yields erroneous results and (b) data-related issues can lead to non-convergence of the model (Kline, 2011). Therefore, it was imperative that the researcher screened that data to ensure they were useable, valid, and reliable for statistical analysis and modeling.

Missing Data

Datasets often have missing data (Brown, 2006; Kline, 2011; Newman, 2014) that can be attributed to several reasons, including but not limited to, hardware failures, participant non-response (Kline, 2011; Newman, 2014), and participant attrition (Kline, 2011). Missing data affects the statistical analyses (Schumacker & Lomax, 2004) and the generalizability of the results (Brown, 2006; Hair et al., 2006; Kline, 2011). Accordingly, the researcher screened the HSLS:09 dataset for missing data using the SPSS Missing Value Analysis (MVA) procedure to identify missing data patterns and to determine the appropriate remedy. The MVA function in SPSS uses univariate statistics, correlations, and covariances to identify patterns of missing data and to establish the rationale for the missing data (IBM, 2014).

Researchers can use several methods to handle missing data (Brown, 2006, Kline, 2011; Newman, 2014). For example, a researcher can delete missing data listwise or pairwise and use only complete data; however, these methods skew results. Some researchers have admonished against these deletion methods (Baraldi & Enders, 2009). Another method is mean substitution...
whereby missing data are replaced with the overall sample mean (Kline, 2011). Tabachnick and Fidell (2001) recommended mean substitution for large datasets with 5% or less missing data. However, Kline (2011) noted that mean substitution distorts data distribution by reducing variability. Another technique to handle missing data is imputing the missing values using model-based imputation methods (Allison, 2003; Baraldi & Enders, 2009; Brown, 2006; Kline, 2011; Newman, 2014).

Typically, model-based imputation methods replace missing data with regressed predicted plausible values based on the missing data patterns (Brown, 2006; Kline, 2011). Model-based imputation methods include but are not limited to, Expectation-Maximization (EM) algorithm, Maximum Likelihood (ML), Full Information Maximum Likelihood (FIML), and Multiple Imputation (MI). Researchers used EM widely for CFA and SEM analyses prior to the introduction of ML and FIML (Brown, 2006). However, Brown (2006) cautioned that EM yields parameter estimates with inconsistent standard errors. Conversely, ML imputes plausible data values that yield consistent standard errors in CFA and SEM analyses. Therefore, ML imputation methods are regarded as the best imputation methods in SEM (Allison, 2003; Baraldi & Enders, 2009; Brown, 2006; Kline, 2011; Newman, 2014).

Outliers

Kline (2011) defined outliers as scores that are extremely different from the rest of the data. In normally distributed data, $z$-scores above 3.0 in absolute value are considered potential outliers (Kline, 2011; Stevens, 2002). In univariate normally distributed data, researchers have suggested using frequency distributions of each study item to identify potential outliers (Kline, 2011; Stevens, 2002). In multivariate normally distributed data, Kline (2011) recommended examining the Mahalanobis distance (D) statistic to determine potential outliers. The D statistic
“indicates the distance in standard deviation units between a set of scores (vector) for an individual case and the sample mean for all variables (centroid), correcting for intercorrelations” (Kline, 2011, p. 84).

For this study, the researcher used the Explore procedure in SPSS to determine the D statistic for the study variables. Additionally, the researcher used the Anomaly Detection procedure in SPSS to detect outliers. According to IBM (2014), the Anomaly Detection procedure allows researchers to evaluate response anomalies based on deviations from the sample norms.

Multivariate Normality

One assumption of SEM is that data are multivariate and normally distributed (Brown, 2006; Kline, 2011). Non-normal data influences the regressions coefficients in SEM (Gaston, 2014). Additionally, multivariate normality is a more stringent assumption than univariate normality (Stevens, 2002). While it is difficult to detect multivariate normality, “Normality on each of the variables is a necessary, but not sufficient, condition for multivariate normality to hold” (Stevens, 2002, p. 262). To that end, prior to conducting any analyses, the researcher evaluated normality of the study variables. Descriptive statistics (i.e., mean and standard deviation) were generated and reviewed and kurtosis and skewness were examined to determine the distribution and shape of each variable included in the study. Typically, normal distributions have skewness and kurtosis of zero (Tabachnick & Fidell, 2001). Acceptable skewness values range from -3 to 3 (Brown, 2006; Kline 2011). According to Tabachnick and Fidell (2001), positive kurtosis above zero suggests a highly peaked distribution with short thick tails, and negative kurtosis values is indicative of a distribution that is too flat. These authors upheld that, non-normal kurtosis underestimates the variance of the variables.
The researcher performed tests of multivariate normality on all study variables using an SPSS macro syntax developed and validated by DeCarlo (1997). The researcher also used the macro to conduct Small’s (1980, 1984) multivariate kurtosis and skewness tests on items included in the study and Small’s omnibus test of multivariate normality.

Multicollinearity

Multicollinearity is evident when two items measure the same thing (Kline, 2011). For example, items and constructs with multiple correlations of 1.0 suggest extreme collinearity (Kline, 2011). In addition, moderate to high intercorrelations among predictor variables indicate a multicollinearity problem (Kline, 2011; Stevens, 2002). Brown (2006) stipulated that a completely standardized factor loading with a value above 1.0 might suggest a multicollinearity problem. A non-positive definite CFA and SEM solution might also indicate multicollinearity (Brown, 2006; Kline, 2011). Furthermore, a factor correlation matrix with values greater than 0.85 might indicate a multicollinearity problem (Brown, 2006).

Multicollinearity is problematic because it limits the effect size, confounds the effects of the independent variables, and increases variance of the regression coefficients, which makes the prediction equation unstable (Stevens, 2002). To ascertain whether the current data exhibited multicollinearity, the researcher examined bivariate correlations. In addition, the researcher regressed the study items and the three constructs against the dependent variable to examine the Variance Inflation Factor (VIF) (Kline, 2011; Stevens, 2002). The researcher also examined the CFA and SEM theta-delta matrices to determine whether the study items and constructs exhibited a non-positive definite solution.
Homoscedasticity

Kline (2011) defined homoscedasticity as the uniform distribution among residuals. According to Osborne and Waters (2002), homoscedasticity is evident when “the variance of errors is the same across all levels of the independent variables. When the variance of the errors differs at different values of the independent variables, heteroscedasticity is indicated” (p. 4). Kline contended that heteroscedasticity among residuals could be attributed to non-normality. To check for homoscedasticity and heteroscedasticity, Osborne and Waters recommend generating and visually examining plots of the standardized errors against the Y-hat standardized values. To determine whether the current data exhibited heteroscedasticity, the researcher generated and visually inspected plots of the standardized residuals against the Y-hat standardized scores.

Sample Size

Generally, SEM requires a large sample size (Kline, 2011). The issue of sample size required to specify a CFA is contentious (DiStefano & Hess, 2005; Kline, 2011), and determining the right sample size for latent modeling studies has been an ongoing challenge among researchers (Jackson, Voth, & Frey, 2013). Sample size is crucial because it affects the stability of the parameter estimates (Schreiber, Stage, King, Nora, & Barlow, 2006). Furthermore, small sample sizes increase sampling error for variances and covariances that often lead to fit indices and convergence failures (Jackson et al., 2013; Kline, 2011).

Jackson (2003) evaluated the $N:q$ rule empirically and recommended that researchers evaluate sample size in terms of the ratio of $N$ to the number of parameters ($q$) to be estimated. His conclusion that an ideal $N$ to $q$ ratio is 20:1. The results of Bollen’s (1989) simulation studies suggest an $N:p$ ratio of 5:1. Other studies have indicated that sample size should be a minimum
of 200 for a model to yield robust inferences based on the non-central Chi square distribution (Herzog & Boomsma, 2009). Curran, Boleyn, Chen, Paxton, and Kirby (2003) found unbiased results across all three models tested using sample sizes of \( n = 200 \) and greater. Generally, the rule of thumb is a sample size of no less than 200 (Bollen, 1989). In addition to using the \( N:q \) rule to verify sample size, the researcher examined Hoelter’s critical \( N \) index reported in the model fit indices. Hoelter’s critical \( N \) stipulates the largest sample for which to accept the hypothesis that the model fits the data (Hoelter, 1983).

### Sampling Weights

Data from the HSLS:09 were collected using complex sampling techniques (Ingels et al., 2011). Complex sampling poses challenges that must be addressed prior to conducting any statistical analyses to obtain precise standard errors and parameter estimates (Hahs-Vaughn, 2005). Hahs-Vaughn (2005) and Osborne (2011) recommend using best practices by applying appropriate weights and design effects to generate a sample that is generalizable to the target population. The NCES provided a number of sampling weights to account for the complex sampling design so analyses could be generalizable to the target population. The researcher used the W1STUDENT weights to account for sampling and non-response biasness (Ingels et al., 2011). Ingels et al. (2011) upheld that the W1STUDENT weights consider the base-year student non-response and that these weights are associated with the target population of ninth-grade students.

### Data Analytic Steps

After screening the data and evaluating the assumptions for conducting SEM analyses, the researcher proceeded with the statistical analyses. Univariate summary statistics were initially computed for the study items. Next, the researcher generated a correlation matrix to
evaluate the bivariate relationships between the study variables. Regarding the magnitude of the absolute value of the correlation coefficient, a small or slight correlation ranges from 0 to 0.30, a moderate correlation ranges from 0.31 to 0.50, and a strong correlation ranges from 0.51 to 1.0 (Cohen, 1988).

Granted that minimal literature exists on the relation between study items and constructs, the researchers subjected the raw data to exploratory factor analysis to evaluate the structure of the latent variables empirically. Next, the researcher subjected the correlation and covariance matrices to CFA. EFA and CFA were conducted using a cross-validation technique recommended by Byrne, Shavelson, and Muthén (1989). The researcher then evaluated the latent constructs for reliability and validity. Cronbach’s alpha and Construct Reliability (CR) were used to examine the reliability of the scales. The researcher conducted Average Variance Extracted (AVE) analyses to determine convergent and discriminant validity of the constructs (Fornell & Larcker, 1981; Hair et al, 2006). Finally, the researcher specified and estimated a structural equation model to determine the influence of the hypothesized relationships on the total analytical sample.

Exploratory Factor Analysis

Based on a thorough literature review and the theoretical framework, the researcher reviewed and identified 12 items that hypothetically measured the latent variables. The 12 items were subjected to EFA to evaluate the structure of the latent variables empirically. The EFA is considered as “one of the most powerful methods yet for reducing variable complexity to greater simplicity” (Kerlinger, 1979, p. 180). According to Thompson (2004), factor analysis is used (a) to validate scores or item responses, (b) to develop or confirm a theory regarding the underlying constructs, or (c) to identify relationships among study items.
In the current study, the researcher used EFA to identify the latent constructs and as a pivotal precursor to CFA to develop and refine the measurement model (Brown, 2006). The researcher factor analyzed the study items using principal component analysis (PCA) with a Varimax orthogonal rotation to identify the structure of the latent constructs. The PCA was chosen because it uses the overall variance of each variable to examine the variance shared between variables (Kieffer, 1999). In Varimax rotation, “factors are cleaned up so that ideally every observed variable has a noteworthy factor pattern/structure coefficient on only one of the factors” (Kieffer, 1999, p. 80).

Confirmatory Factor Analysis

Typically, CFA is used as a prelude to SEM models that delineate structural relationships among latent constructs (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Blunch, 2013; Brown, 2006; Harrington, 2009; Kline, 2011). Confirmatory factor analysis assists the researcher in ascertaining relationships between latent variables and underlying indicators (Harrington, 2009). According to Brown (2006), CFA serves four main purposes: (a) evaluation of the psychometric properties of a scale, (b) validity of latent constructs, (c) measurement invariance, and (d) evaluation of method effects.

The researcher used CFA to evaluate the psychometric properties and the validity of the scales. A 3-factor model was specified using polychoric correlation and asymptotic covariance matrices (Brown, 2006; Forero et al., 2009; Jöreskog & Sörbom, 2004; Kline, 2011; Nye & Drasgow, 2011; Schumacker & Lomax, 2004) for ordinal scaled and non-normal data, respectively. The researcher specified a 3-factor CFA model in which four items that evaluated students’ beliefs and confidence in math (MEFF2 to MEFF5) were loaded on the latent variable of self-efficacy. Three items (HWK1 to HWK3) that measured the amount of time students
devoted to homework and studying in a typical day were loaded on the latent construct academic engagement. Five items that measured how math teachers interacted with their students (TCR1 to TCR5) were loaded on the latent variable student-teacher relationships. Initially, all parameters were freely estimated. A review of the modification indices suggested that correlating items TCR4 and TCR5 might improve the model fit. Thus, these items were correlated in all subsequent CFA and SEM analyses.

Cross-Validation of EFA and CFA analyses

The researcher conducted EFA and CFA using a cross-validation technique. Cross-validation entails randomly generating two subsamples (Byrne et al., 1989). To this end, the researcher randomly sampled and placed study participants into two groups (Group 1 and Group 2). The researcher conducted an EFA on Group 1 and a CFA on Group 2, and then a CFA on the total sample to confirm the underlying latent variable structure obtained from the Group 2 CFA analyses.

Reliability of the Latent Constructs

Crocker and Algina (2006) cautioned, “When selecting [an instrument] for a specific purpose, [the researcher] has a clear responsibility to ascertain that the [instrument] has validation evidence appropriate to the intended use in the local situation” (p. 218). They upheld that reliability is a property of the scores on an instrument for a particular group of examinees. Brown (2006) recommended that latent constructs be evaluated to ensure they measure what they are expected to measure reliably. Brown noted, “Reliability refers to the precision or consistency of measurement; that is, the overall proportion of true score variance to total observed variance of the measure” (p. 337).
Although there is considerable debate on the best reliability measure in SEM, Hair et al. (2006) contended that the Cronbach’s alpha coefficient is still widely used. In addition to the Cronbach’s alpha, they suggested evaluating the CR. Accordingly, the researcher determined the internal consistencies of the latent constructs by calculating both Cronbach’s alpha and the CR coefficient for each of construct. Construct reliability was calculated from the squared sum of factor loadings for each construct and the sum of the error variance terms for each construct (Hair et al., 2006).

Validity of the Latent Constructs

Evaluating the reliability of the factor structure alone is not sufficient; the factor structures must also be valid. Validity implies that factors measure what they are supposed to measure (Blunch, 2013; Brown, 2006; Hair et al., 2006). Irrespective of whether one is working with an established scale or developing a new one, Hair et al. (2006) cautioned that construct validity should be checked carefully before calculating the structural estimates of the SEM model. Simply stated, factor structures should possess acceptable convergent and discriminant validity.

The researcher used CFA to assess the construct validity of the measurement model. Hair et al. (2006) noted, “Construct validity is the extent to which a set of measured items actually reflects the theoretical latent construct those items are designed to measure” (p. 776). Evaluation of construct validity of the scales provides evidence that the items study participants responded to measure the true score of the target population. Thus, the researcher evaluated the convergent and discriminant validity of the study constructs using Analysis of Variance Extracted (AVE).
Convergent and discriminant validity entails assessing measures against each other as opposed to against an external standard (Kline, 2011). Convergent validity is established when a set of variables measure the same construct. In contrast, discriminant validity is evident when manifest indicators measure different constructs (Hair et al., 2006; Kline, 2011). With convergent validity, constructs exhibit moderate intercorrelations, while with discriminant validity, constructs are expected to depict low intercorrelations (Kline, 2011). The researcher examined the factor pattern/structure coefficients using AVE $\theta^2$ analyses to evaluate the convergent validity of the latent constructs (Hair et al., 2006). The standardized pattern/structure estimates and AVE values of 0.50 or greater suggest adequate convergence (Fornell & Larcker, 1981; Hair et al., 2006). Convergent validity below 0.50 indicates that manifest items do not correlate well with each other within the constructs; thus, the latent constructs are not fully explained by the underlying items (Hair et al., 2006).

The researcher also evaluated the discriminant validity of the constructs using AVE analyses. According to Hair et al. (2006), higher variance extracted than the squared correlation estimates among constructs exhibits discriminant validity. They also suggested calculating the Maximum Shared Variance (MSV) and Average Shared Variance (ASV) indices. For a measurement model with good discriminant validity, the MSV and ASV should be less than the AVE. Inadequate discriminant validity would indicate that the manifest variables correlate highly with other variables outside the proposed constructs, which could imply that the constructs did not measure what they are purported to measure (Hair et al., 2006).

Structural Equation Model Analysis

The researcher determined the relationship of the three constructs to ninth-grade male students’ Algebra I achievement. Student achievement was measured by students’ IRT scale
scores on the Algebra I assessment administered in fall 2009. Simultaneously, including all constructs in the model helped the researcher ascertain which construct exerted the greatest influence on Algebra I achievement among ninth-grade African American male students. The researcher hypothesized direct and indirect effects of the independent variables on the dependent variable to advance Bandura’s SCT, which postulates that human learning is a triad and complex interaction between personal (cognitive-affective), behavioral, and environmental determinants.

Evaluation of CFA and SEM Model Fit Indices

To determine whether the measurement and structural models represented the data adequately, the researcher examined the model global fit indices for all specified and estimated models. The researcher used Chi square to evaluate whether the model fit the data (Brown, 2006; Byrne, 1998; Hair et al., 2006; Nye & Drasgow, 2011). Sample size, non-normal data, and complexity of the model influence the Chi square statistic (Byrne, 1988; Hair et al., 2006). Accordingly, Brown (2006) recommended examining a number of fit indices to compliment the Chi square statistic. Three types of fit indices are typically used to evaluate the fit of the model to the data: (a) absolute fit, (b) parsimony correction, and (c) comparative fit indices (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Brown, 2006; Hair et al., 2006; Hu & Bentler, 1999; Kline, 2011).

Absolute Fit Indices

Absolute fit indices are used to examine whether the predicted variance-covariance matrix is equivalent to the sample variance-covariance matrix (Byrne, 1998; Harrington, 2009; Kline, 2011). Usually, absolute fit indices are interpreted as proportions of the sample data matrix covariance accounted for by the model (Kline, 2011). Chi square ($\chi^2$) is the most commonly used absolute fit index and it ascertains whether the model fits the population
Harrington, 2009). Other absolute fit indices include Root Mean Square Residual (RMR), which indicates the average inconsistency between the input and predicted covariances, and the Standardized Root Mean Square Residual (SRMR), which evaluates the variation between the correlation input and correlation predicted by the model (Brown, 2006). According to Hair et al. (2006), SRMR of < 0.09 indicates a good model fit. Kline (2011) suggested that SRMR of < 0.10 with corresponding 90% confidence intervals is acceptable.

Parsimony Correction Indices

Parsimony correction indices are used to evaluate the extent to which the model fits the population (Harrington, 2009). The Root Mean Square Error of Approximation (RMSEA) is used to determine whether the specified model fits the population. An RMSEA of < 0.05 indicates a good fit, 0.05 to 0.10 suggests moderate fit, and > 0.10 suggests poor model fit (Hair et al., 2006; Kline, 2011). Conversely, Brown (2006) suggested that an RMSEA of < 0.06 is a good model fit.

Comparative Fit Indices

Comparative fit indices allow the researcher to assess model fit compared to a more restricted or nested baseline model (Harrington, 2009). Examples of comparative fit indices include the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and the Non-normed Fit Index (NNFI). According to Kline (2011), CFI of 0.90 and above indicates good model fit. For the current study, the researcher examined the Chi square statistic, parsimony correction indices, and comparative fit indices to evaluate all specified and fitted models.

Summary

Chapter 3 included a description of the causal-comparative method used to examine the influence of self-efficacy, academic engagement, and student-teacher relationships on Algebra I
achievement among ninth-grade African American male students. The researcher identified the dependent and independent variables and outlined their operational definitions. Finally, the researcher discussed the data analytic techniques and steps in detail. The results of the analyses are presented in Chapter 4.
CHAPTER 4

RESULTS

The researcher aimed to discern the effects of self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement among ninth-grade African American male students across the United States. Study participants included 697 African American male ninth-grade students. The W1STUDENT sampling weights provided by the National Center for Education Statistics (NCES) yielded a target population \( N = 180,711 \). The researcher used structural equation modeling (SEM) to analyze the data. Structural equation modeling is a robust statistical technique used to specify and estimate hypothesized models of relationships between observed and unobserved variables (Hair et al., 2006; Kline, 2011; Schumacker & Lomax, 2004) and to account for measurement error (Hair et al., 2006). The researcher sought to answer the following questions:

1. Is self-efficacy related to Algebra I achievement among ninth-grade African American male students across the United States?

2. Is academic engagement related to Algebra I achievement among ninth-grade African American male students across the United States?

3. Are student-teacher relationships related to Algebra I achievement among ninth-grade African American male students across the United States?

The researcher conducted the following steps for the data analyses: (1) evaluated SEM assumptions, (2) conducted an exploratory factor analysis (EFA), (3) specified and estimated a measurement model, (4) evaluated construct reliability and validity, and (5) tested the hypothesized structural relationships. This chapter reports the findings of these analyses.
Descriptive Statistics and Tests of Statistical Assumptions

As outlined in Chapter 3, SEM has several assumptions that must be evaluated prior to conducting analyses. In addition to screening data for missing values, the researcher calculated outliers, multivariate normality, collinearity, homoscedasticity, sample size adequacy, and basic descriptive statistics (Brown, 2006; Hair et. al., 2006; Kline, 2011; Harrington, 2009). Table 4.1 listed the means, standard deviations ($SD$), variance, and minimum and maximum values for each variable included in the study. The means for self-efficacy items ranged from 2.76 to 3.10 ($SD = 0.71$ to 0.79). The means for the academic engagement items ranged from 1.38 to 1.66 ($SD = 0.73$ to 0.91), and those for student-teacher relationships items ranged from 3.05 and 3.21 ($SD = 0.80$ to 0.89). Algebra I achievement had a mean of 45.04 ($SD = 9.4$).

Self-efficacy items revealed moderate to high means, which suggest that participants were confident in understanding math assignments and textbooks and in passing math tests. Likewise, student-teacher relationships means were moderate to high. The majority of participants agreed that their math teachers treated them with respect, fairly, and valued or listened to their ideas. Conversely, the means for items measuring academic engagement were low. These low means imply that respondents devoted considerably less time to homework and studying; therefore, they were academically disengaged.
Table 4.1

**Univariate summary Statistics for the Study Variables (n = 697; Weighted N = 180,711)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
<th>Skew</th>
<th>Kurt</th>
<th>Min. Freq.</th>
<th>Max</th>
<th>Max Freq.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Self-Efficacy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF2</td>
<td>3.05</td>
<td>0.74</td>
<td>0.55</td>
<td>-0.53</td>
<td>0.17</td>
<td>1.0</td>
<td>5,468</td>
<td>4.0</td>
</tr>
<tr>
<td>MEFF3</td>
<td>2.76</td>
<td>0.77</td>
<td>0.59</td>
<td>-0.20</td>
<td>-0.39</td>
<td>1.0</td>
<td>9,425</td>
<td>4.0</td>
</tr>
<tr>
<td>MEFF4</td>
<td>3.03</td>
<td>0.74</td>
<td>0.55</td>
<td>-0.61</td>
<td>0.48</td>
<td>1.0</td>
<td>6,717</td>
<td>4.0</td>
</tr>
<tr>
<td>MEFF5</td>
<td>3.10</td>
<td>0.71</td>
<td>0.50</td>
<td>-0.67</td>
<td>0.79</td>
<td>1.0</td>
<td>5,672</td>
<td>4.0</td>
</tr>
<tr>
<td><strong>Academic Engagement</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1</td>
<td>1.66</td>
<td>0.91</td>
<td>0.83</td>
<td>1.71</td>
<td>3.42</td>
<td>1.0</td>
<td>97,610</td>
<td>6.0</td>
</tr>
<tr>
<td>HWK2</td>
<td>1.53</td>
<td>0.91</td>
<td>0.83</td>
<td>2.62</td>
<td>8.91</td>
<td>1.0</td>
<td>114,294</td>
<td>6.0</td>
</tr>
<tr>
<td>HWK3</td>
<td>1.38</td>
<td>0.73</td>
<td>0.53</td>
<td>3.04</td>
<td>13.16</td>
<td>1.0</td>
<td>126,880</td>
<td>6.0</td>
</tr>
<tr>
<td><strong>Student – Teacher Relationship</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1</td>
<td>3.15</td>
<td>0.82</td>
<td>0.67</td>
<td>-1.04</td>
<td>0.96</td>
<td>1.0</td>
<td>12,260</td>
<td>4.0</td>
</tr>
<tr>
<td>TCR2</td>
<td>3.05</td>
<td>0.89</td>
<td>0.79</td>
<td>-0.88</td>
<td>0.21</td>
<td>1.0</td>
<td>16,310</td>
<td>4.0</td>
</tr>
<tr>
<td>TCR3</td>
<td>3.05</td>
<td>0.87</td>
<td>0.76</td>
<td>-0.80</td>
<td>0.13</td>
<td>1.0</td>
<td>13,848</td>
<td>4.0</td>
</tr>
<tr>
<td>TCR4</td>
<td>3.21</td>
<td>0.80</td>
<td>0.64</td>
<td>-0.96</td>
<td>0.64</td>
<td>1.0</td>
<td>8,614</td>
<td>4.0</td>
</tr>
<tr>
<td>TCR5</td>
<td>3.08</td>
<td>0.82</td>
<td>0.67</td>
<td>-0.84</td>
<td>0.47</td>
<td>1.0</td>
<td>11,451</td>
<td>4.0</td>
</tr>
<tr>
<td><strong>Algebra I Achievement</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSCORE</td>
<td>45.04</td>
<td>9.54</td>
<td>91.01</td>
<td>0.26</td>
<td>-0.20</td>
<td>24.4</td>
<td>53</td>
<td>82.2</td>
</tr>
</tbody>
</table>

**Missing Data**

The researcher used the SPSS Missing Value Analysis (MVA) procedure to identify missing data patterns. The MVA procedure is used to estimate means, covariances, and correlation coefficients to identify missing data by variable and corresponding patterns (IBM, 2014). Approximately 71% of participants responded to all 12 study items (n = 664; 71.2%). The extent of missing data ranged from 7.4% for HWK1 to 30.9% for HWK3. Table 4.2 includes the descriptive statistics for cases with valid data values and the percentage of observations with missing data for each variable. The researcher used Little’s MCAR test to evaluate whether the data were missing completely at random. According to Hair et al. (2006), Little’s MCAR test is used to compare actual patterns of missing data with expected values to
determine whether the missing data were completely randomly distributed. The analysis yielded a significant result, Little’s MCAR test $\chi^2 = 588.71$, $df = 460$, $p = .000$, which indicates that the data were not missing completely at random (Hair et al., 2006).

Table 4.2

*Missing Value Analysis Summary by Study Variables*

<table>
<thead>
<tr>
<th>Study Variables</th>
<th>Missing</th>
<th>Valid N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Percent</td>
</tr>
<tr>
<td><strong>Self-Efficacy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF2</td>
<td>171</td>
<td>18.3</td>
</tr>
<tr>
<td>MEFF3</td>
<td>177</td>
<td>19.0</td>
</tr>
<tr>
<td>MEFF4</td>
<td>182</td>
<td>19.5</td>
</tr>
<tr>
<td>MEFF5</td>
<td>178</td>
<td>19.1</td>
</tr>
<tr>
<td><strong>Academic Engagement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1</td>
<td>69</td>
<td>7.4</td>
</tr>
<tr>
<td>HWK2</td>
<td>194</td>
<td>20.8</td>
</tr>
<tr>
<td>HWK3</td>
<td>288</td>
<td>30.9</td>
</tr>
<tr>
<td><strong>Student – Teacher Relationships</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1</td>
<td>184</td>
<td>19.7</td>
</tr>
<tr>
<td>TCR2</td>
<td>184</td>
<td>19.7</td>
</tr>
<tr>
<td>TCR3</td>
<td>180</td>
<td>19.3</td>
</tr>
<tr>
<td>TCR4</td>
<td>182</td>
<td>19.5</td>
</tr>
<tr>
<td>TCR5</td>
<td>181</td>
<td>19.4</td>
</tr>
</tbody>
</table>

Little’s MCAR Test $\chi^2 = 588.71$, $df = 460$, $p = .000$

Data Imputation

As discussed in Chapter 3, the Full Information Maximum Likelihood (FIML) estimation is recommended to handle missing data in SEM analyses (Allison, 2003; Baraldi & Enders, 2009; Brown, 2006; Kline, 2011; Newman, 2014). To that end, the researcher imputed missing data with plausible values in LISREL using the FIML estimation before generating the correlation and covariance matrices subjected to confirmatory factor analyses (CFA) and SEM. The FIML estimation successfully imputed about 14% of the cases ($n = 33$) with incomplete data.
data. The software could not impute 231 cases because participants did not respond to over 15% of the study variables.

Outliers

The Mahalanobis distance (D) analysis was used to identify cases with the largest contribution to the Mardia’s coefficient; five multivariate outliers were detected and deleted ($p < .000$). The SPSS Anomaly Detection procedure did not identify any cases with deviations above a z-score of 3. The researcher performed subsequent analyses on 697 participants.

Multivariate Normality

The researcher computed univariate statistics in PRELIS 2.30 (Jöreskog & Sörbom, 1996) to evaluate the skewness and kurtosis of the weighted variables (see Table 4.1). The data revealed that most study variables had skewness within the acceptable range of -3 to 3 (Brown, 2006; Kline, 2011). Kurtosis values for self-efficacy and student-teacher relationships hovered around zero indicating that these constructs were normally distributed (Tabachnick & Fidell, 2001). The kurtosis values for HWK1, HW2, and HWK3 (academic engagement) were above 3.0; consequently, the data were non-normal. It is worth noting that HWK2 and HWK3 items in the academic engagement construct had considerably high skewness values. These data suggest that most participants spent less than an hour in a typical school day completing homework or studying outside of school. Conversely, more students reported that they had high math self-efficacy and better relationships with their teachers. Therefore, the data were not normally distributed. Because the data violated the normality assumption, the researcher generated asymptotic covariance matrices (Brown, 2006; Forero et al., 2009; Kline, 2011; Schumacker & Lomax, 2004).
Tests of Multivariate Normality

The results of tests of multivariate normality analyses are summarized in Table 4.3. All data obtained from the multivariate normality tests yielded significant alpha values of .0000. These findings indicate that the data did not meet the assumption of multivariate normality. Therefore, the researcher used the Robust Maximum Likelihood (MLR) estimation method to estimate the CFA and SEM models (Jöreskog & Sörbom, 2004).

Table 4.3

Tests of Multivariate Skewness, Kurtosis, and Normality (n= 697)

<table>
<thead>
<tr>
<th>Test</th>
<th>Value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small’s Test of Multivariate Skewness</td>
<td>726.70</td>
<td>.0000</td>
</tr>
<tr>
<td>Srivastava’s Test of Multivariate Skewness</td>
<td>529.90</td>
<td>.0000</td>
</tr>
<tr>
<td>Small’s Test of Multivariate Kurtosis</td>
<td>296.18</td>
<td>.0000</td>
</tr>
<tr>
<td>Srivastava’s Test of Multivariate Kurtosis</td>
<td>5.78</td>
<td>.0000</td>
</tr>
<tr>
<td>Mardia’s Test of Multivariate Kurtosis</td>
<td>293.51</td>
<td>.0000</td>
</tr>
<tr>
<td>Small’s Test of Omnibus Test of Multivariate Normality</td>
<td>1022.88</td>
<td>.0000</td>
</tr>
</tbody>
</table>

Multicollinearity

The researcher generated a correlation matrix to evaluate the bivariate relationships between study variables. Table 4.4 shows the inter-item correlation matrix for the variables. The table also provides a list of study items by construct, mean, and SD calculated using LISREL 9.2. The data presented are based on participants with complete data and the 33 cases that were successfully imputed using the FIML estimation method. Examination of the bivariate correlations shows that most items in the self-efficacy and student-teacher relationships constructs exhibited moderate to high correlation coefficients; nonetheless, no variable exhibited a correlation coefficient above 0.90 (Kline, 2011). The academic engagement construct items had very low (-0.03) to moderate (0.57) correlation coefficients. Accordingly, no variable exhibited collinearity as evaluated in the bivariate correlation analyses.
### Table 4.4

*Inter-Item Correlations, Univariate Summary Statistics for Manifest Items and Dependent Variable (N=697, Weighted Sample = 180, 711)*

<table>
<thead>
<tr>
<th>Item</th>
<th>MEFF 2</th>
<th>MEFF 3</th>
<th>MEFF 4</th>
<th>MEFF 5</th>
<th>TCR 1</th>
<th>TCR 2</th>
<th>TCR 3</th>
<th>TCR 4</th>
<th>TCR 5</th>
<th>HWK 1</th>
<th>HWK 2</th>
<th>HWK 3</th>
<th>MSCORE</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEFF2</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF3</td>
<td>0.641</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF4</td>
<td>0.657</td>
<td>0.573</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF5</td>
<td>0.753</td>
<td>0.595</td>
<td>0.684</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1</td>
<td>0.272</td>
<td>0.259</td>
<td>0.268</td>
<td>0.273</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR2</td>
<td>0.250</td>
<td>0.263</td>
<td>0.260</td>
<td>0.242</td>
<td>0.863</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR3</td>
<td>0.301</td>
<td>0.271</td>
<td>0.283</td>
<td>0.287</td>
<td>0.821</td>
<td>0.760</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR4</td>
<td>0.272</td>
<td>0.188</td>
<td>0.268</td>
<td>0.306</td>
<td>0.755</td>
<td>0.701</td>
<td>0.692</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR5</td>
<td>0.322</td>
<td>0.246</td>
<td>0.283</td>
<td>0.309</td>
<td>0.671</td>
<td>0.616</td>
<td>0.646</td>
<td>0.659</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1</td>
<td>0.006</td>
<td>0.026</td>
<td>0.034</td>
<td>0.069</td>
<td>0.033</td>
<td>0.035</td>
<td>0.019</td>
<td>0.029</td>
<td>0.084</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK2</td>
<td>-0.022</td>
<td>0.021</td>
<td>-0.020</td>
<td>-0.033</td>
<td>0.030</td>
<td>0.045</td>
<td>0.012</td>
<td>0.008</td>
<td>0.034</td>
<td>0.570</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK3</td>
<td>0.103</td>
<td>0.096</td>
<td>0.053</td>
<td>0.087</td>
<td>0.058</td>
<td>0.049</td>
<td>0.039</td>
<td>0.057</td>
<td>0.080</td>
<td>0.484</td>
<td>0.530</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSCORE</td>
<td>0.219</td>
<td>0.183</td>
<td>0.223</td>
<td>0.223</td>
<td>0.168</td>
<td>0.140</td>
<td>0.120</td>
<td>0.190</td>
<td>0.200</td>
<td>0.023</td>
<td>-0.043</td>
<td>0.013</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>3.05</td>
<td>2.76</td>
<td>3.03</td>
<td>3.10</td>
<td>3.15</td>
<td>3.05</td>
<td>3.05</td>
<td>3.21</td>
<td>3.08</td>
<td>1.66</td>
<td>1.53</td>
<td>1.38</td>
<td>45.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>0.74</td>
<td>0.79</td>
<td>0.74</td>
<td>0.71</td>
<td>0.82</td>
<td>0.89</td>
<td>0.87</td>
<td>0.80</td>
<td>0.82</td>
<td>0.91</td>
<td>0.91</td>
<td>0.73</td>
<td>9.54</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


In addition to the bivariate correlation analyses, the researcher regressed study items and factor scores against the dependent variable to evaluate collinearity statistics. The researcher also scrutinized the Variance Inflation Factor (VIF) scores to establish whether study items and factor scores exhibited multicollinearity. The collinearity statistics obtained from the analyses are displayed in Table 4.5. All multiple regression analyses yielded VIF scores of less than 4, which were below the acceptable threshold of 10 (Stevens, 2002).

Table 4.5

Collinearity Statistics Summary for Study Variables and Factor Scores

<table>
<thead>
<tr>
<th>Study Item</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Self-Efficacy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF2</td>
<td>0.412</td>
<td>2.428</td>
</tr>
<tr>
<td>MEFF3</td>
<td>0.547</td>
<td>1.827</td>
</tr>
<tr>
<td>MEFF4</td>
<td>0.478</td>
<td>2.093</td>
</tr>
<tr>
<td>MEFF5</td>
<td>0.434</td>
<td>2.303</td>
</tr>
<tr>
<td><strong>Academic Engagement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1</td>
<td>0.553</td>
<td>1.807</td>
</tr>
<tr>
<td>HWK2</td>
<td>0.543</td>
<td>1.843</td>
</tr>
<tr>
<td>HWK3</td>
<td>0.525</td>
<td>1.906</td>
</tr>
<tr>
<td><strong>Student-Teacher Relationships</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1</td>
<td>0.271</td>
<td>3.697</td>
</tr>
<tr>
<td>TCR2</td>
<td>0.328</td>
<td>3.046</td>
</tr>
<tr>
<td>TCR3</td>
<td>0.369</td>
<td>2.709</td>
</tr>
<tr>
<td>TCR4</td>
<td>0.442</td>
<td>2.260</td>
</tr>
<tr>
<td>TCR5</td>
<td>0.506</td>
<td>1.975</td>
</tr>
<tr>
<td><strong>Factor Scores</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor 1</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Factor 2</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Factor 3</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

An evaluation of the factor correlation matrices for the cross-validation and total analytical samples (see Tables 4.8 and 4.9) revealed that no correlation among the latent
variables was greater than the 0.85 criteria (Brown, 2006). The CFA and SEM theta-delta matrices yielded positive definite solutions. Consequently, the multicollinearity assumption was not violated.

Homoecdasticity

The researcher generated and visually inspected item- and construct-level plots of the standardized errors against the Y-hat standardized values to check for the homoscedasticity assumption. Visual inspection of the plots indicated that the residuals of the self-efficacy and student-teacher relationships items were evenly randomly scattered around the mean of the Y-hat standardized scores. In contrast, residuals of the academic engagement items were heterogeneously scattered around the mean of the Y-hat standardized scores. These findings suggest that the variances were homogeneous for the self-efficacy and student-teacher relationships constructs, but were heterogeneous for the academic engagement construct. Therefore, these data violated the homoscedasticity assumption. As Kline (2011) noted, the violation of this assumption is indicative of non-normal data.

Sample Size

The researcher used Jackson’s (2003) suggested rule of \( N \) to \( q \) ratio of 20:1, Bollen’s (1989) \( N \) to \( q \) ratio of 5:1, and Hoelter’s critical \( N \) value to determine the necessary sample size for the current study. Jackson’s ratio indicated that 560 participants were adequate for the measurement phase of the study. Bollen’s ratio yielded a sample size of 140 for the CFA. Hoelter’s critical \( N \) revealed that a sample size of 446 would be adequate for the current study. Jackson’s ratio also indicated that 620 participants were adequate for the structural phase of the study. Bollen’s ratio suggested that 155 respondents were adequate for the SEM phase of the study. Hoelter’s critical \( N \) indicated that 450 participants were adequate for the study. Using
these recommendations and Hoelter’s critical $N$, the researcher determined that a sample size of 697 would be sufficient for both the CFA and SEM analyses.

Exploratory Factor Analysis Findings

The randomly sampled cross-validation sample was subjected to EFA to evaluate the structure of the latent constructs empirically using SPSS version 23. Prior to examining the potential factors, the researcher screened the data to ensure they were appropriate for the analyses. Specifically, the researcher examined the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s test of sphericity Chi square. The evaluation of these two assumptions yielded a KMO measure of 0.85 and a Bartlett’s test of sphericity Chi square of 421.62 ($df = 66$; $p < .000$). Thus, the data met the basic assumptions to conduct an EFA (Cerny & Kaiser, 1977).

Initially, the researcher subjected all questionnaire items to Principal Component Analysis (PCA) with Varimax orthogonal rotation to identify the latent constructs. The initial EFA analysis yielded eight constructs. Next, the researcher selected 15 items that seemed logically related to the study and conducted another EFA. The second analysis revealed three constructs; however, three items had factor loadings of less than .40. Finally, the researcher conducted an EFA using 12 items with factor loadings above .40. Table 4.6 provides the factor loadings for the 12 study items, the factors extracted, and the corresponding amount of variance reproduced by each factor.

As shown in Table 4.6, all study items had factor loadings of 0.70 and higher. Five items loaded on Factor 1 (student-teacher relationships) and accounted for 30.52% of the variance. The PCA with Varimax rotation yielded one component. An inspection of the scree plot also supported the one component interpretation. The Cronbach’s alpha coefficient for this construct
was 0.91, which is above Nunnally’s (1978) recommended value of 0.70. Four items loaded on Factor 2 (self-efficacy), which explained 23.9% of the variance. The PCA with Varimax rotation yielded one component. An inspection of the scree plot supported the one component interpretation. The Cronbach’s alpha coefficient for this construct was 0.87.

Three items loaded on Factor 3 (academic engagement) and accounted for 18.38% of the variance extracted. The PCA with Varimax rotation for academic engagement revealed one component. An examination of the scree plot supported the one component interpretation. The Cronbach’s alpha coefficient for this construct was 0.83. Overall, the three factors accounted for 72.80% of the total variance extracted. The internal consistencies of these constructs, as measured by Cronbach’s alpha, were above Nunnally’s (1978) recommended value of 0.70. An examination of the scree plot suggested that the 12 items measured the three constructs.

Confirmatory Factor Analysis Findings

Based on the literature review and the assumptions of SCT, the researcher estimated a 3-factor model in LISREL 9.2 in which the math self-efficacy, academic engagement, and student-teacher relationships latent variables were included. Figure 4.1 illustrates the CFA model, latent constructs, and the underlying observed items. The straight single-headed arrows show the factor loadings of the 12 observed variables on the latent variables, and the double-headed arrows depict the covariances among study constructs.

The researcher subjected the three latent constructs with their underlying indicators to SEM CFA (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Byrne, 1998). As noted in Chapter 3, CFAs were conducted for the randomly sampled cross-validation as well as for the total analytical samples. The researcher specified and estimated the 3-factor measurement model
using the MLR estimation method because the data violated the normality assumption (Jöreskog & Sörbom, 2004).

Table 4.6

*Exploratory Factor Analysis: Randomly Sampled Cross-Validation Sample (n=347) Rotated Factor Structure*

<table>
<thead>
<tr>
<th>Construct/Items</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student-Teacher Relationships</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1 9th-grade math teachers in fall 2009 treat students with respect</td>
<td>0.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR2 9th-grade math teachers in fall 2009 treat every student fairly</td>
<td>0.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR3 9th-grade math teachers in fall 2009 value/listen to students’ ideas</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR4 9th-grade math teachers in fall 2009 think all students can be successful</td>
<td>0.82</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR5 9th-grade math teachers in fall 2009 think mistakes of okay if students learn</td>
<td>0.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Self-Efficacy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF3 Confident 9th graders can do well on the fall 2009 math assignments</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF4 Confident 9th graders can do well on the fall 2009 math tests</td>
<td>0.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF2 Certain 9th graders can master skills in the fall 2009 math course</td>
<td>0.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF5 Certain 9th graders can understand the fall 2009 math textbook</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Academic Engagement</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1 Hours spent on math homework/studying during a typical school day</td>
<td>0.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK2 Hours spent on other homework/studying during a typical school day</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK2 Hours spent on science homework/studying during a typical school day</td>
<td>0.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of variance (total = 72.80%)</td>
<td>30.52</td>
<td>23.90</td>
<td>18.38</td>
</tr>
<tr>
<td>Cronbach’s alpha score</td>
<td>.91</td>
<td>.87</td>
<td>.83</td>
</tr>
</tbody>
</table>

KMO Measure = .85; Barlett’s Test of Sphericity $\chi^2 = 4421.62$, $df = 66$; $p = .000$
Figure 4.1: Measurement model: Hypothesized latent constructs and manifest items.

Reliability of the Study Constructs

The researcher computed Cronbach’s reliability coefficients for each latent variable and examined the construct reliability (Fornell & Larcker, 1981; Hair et al., 2006). The reliability analyses results are shown in Table 4.7 for the cross-validation and total analytical CFA samples. According to these data, the self-efficacy, academic engagement, and student-teacher relationship constructs yielded Cronbach’s alpha scores of 0.865, 0.810, and 0.904, respectively for the cross-validation sample. Similarly, internal consistency values for the total analytical sample were above 0.70. Specifically, the Cronbach’s alpha coefficient for self-efficacy was 0.866, academic engagement was 0.818, and student-teacher relationships was 0.908. These
internal consistency values were above Nunnally’s (1978) recommended value of 0.70 for a reliable instrument.

Construct reliability analyses revealed a CR of 0.877, 0.773, and 0.926 for self-efficacy, academic engagement, and student-teacher relationships, respectively. The total analytical sample yielded almost identical CR values as the cross-validation sample. The internal consistency and construct reliability results suggest that the latent variables had moderate to high internal consistency and construct reliability above the acceptable threshold of 0.70 (Nunnally, 1978) and 0.50 (Fornell & Larcker, 1981). Taken as a whole, the reliability of the study constructs was adequate to conduct an SEM for the hypothesized relationships.

Table 4.7

**Construct Reliability Evaluation for Cross-Validation and Total Analytical Samples**

<table>
<thead>
<tr>
<th>Construct</th>
<th>Cronbach’s Reliability Coefficients</th>
<th>Construct Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cross-Validation Sample</td>
<td>Total Analytical Sample</td>
</tr>
<tr>
<td>Self-Efficacy</td>
<td>0.865</td>
<td>0.866</td>
</tr>
<tr>
<td>Academic Engagement</td>
<td>0.810</td>
<td>0.818</td>
</tr>
<tr>
<td>Student – Teacher Relationships</td>
<td>0.904</td>
<td>0.908</td>
</tr>
</tbody>
</table>

Validity of the Study Constructs

The researcher evaluated the convergent and discriminant validity for the items using Average Variance Extracted (AVE) analyses (Fornell & Larcker, 1981; Hair et al., 2006). Tables 4.8 and 4.9 provide the factor correlation matrices and AVE results for the cross-validation and for the total analytical samples, respectively. The correlation matrices for the latent variables indicated that no construct for cross-validation or the total analytical samples had
correlations above the 0.85 threshold (Brown, 2006). The AVE analyses for all the study construct in both samples revealed values above the 0.50 threshold (Fornell & Larcker 1981; Hair et al., 2006). These values indicated that the manifest items correlated well with each other and suggest that the latent constructs can be fully explained by the underlying items. Overall, the constructs exhibited acceptable convergent validity (Fornell & Larcker 1981; Hair et al., 2006).

The researcher evaluated discriminant validity using the Maximum Shared Variance (MSV) and Average Shared Variance (ASV). The ASV values for each study construct were less than the MSV values (Fornell & Larcker, 1981; Hair et al., 2006). These values suggest that the measurement model had good discriminant validity, which implies that the constructs measured what they were purported to measure. The validity analyses revealed that the constructs had acceptable validity to proceed with SEM of the hypothesized relationships.

Table 4.8

*Construct Validity Evaluation for Cross-Validation Sample: Correlation among Latent Constructs (Ø²): AVE, MSV, and ASV*

<table>
<thead>
<tr>
<th></th>
<th>Self-Efficacy</th>
<th>Academic Engagement</th>
<th>Student-Teacher Relations</th>
<th>AVE</th>
<th>MSV</th>
<th>ASV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-Efficacy</td>
<td>0.801</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Academic Engagement</td>
<td></td>
<td>0.730</td>
<td></td>
<td>0.533</td>
<td>0.023</td>
<td>0.021</td>
</tr>
<tr>
<td>Student-Teacher Relations</td>
<td></td>
<td></td>
<td></td>
<td>0.715</td>
<td>0.194</td>
<td>0.108</td>
</tr>
</tbody>
</table>

63
Table 4.9

**Construct Validity Evaluation for Total Analytical Sample: Correlation among Latent Constructs (Ø2): AVE, MSV, and ASV**

<table>
<thead>
<tr>
<th></th>
<th>Self-Efficacy</th>
<th>Academic Engagement</th>
<th>Student-Teacher Relations</th>
<th>AVE</th>
<th>MSV</th>
<th>ASV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-Efficacy</td>
<td>0.810</td>
<td></td>
<td></td>
<td>0.655</td>
<td>0.130</td>
<td>0.066</td>
</tr>
<tr>
<td>Academic Engagement</td>
<td>0.041</td>
<td>0.729</td>
<td></td>
<td>0.531</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Student-Teacher Relations</td>
<td>0.361</td>
<td>0.055</td>
<td>0.847</td>
<td>0.717</td>
<td>0.130</td>
<td>0.067</td>
</tr>
</tbody>
</table>

Measurement Model Global Fit Indices

Table 4.10 provides the global fit indices for the cross-validation sample and the total analytical sample. All items in the study samples significantly contributed to the latent constructs they measured, as all item factor loadings were above 0.50. Moreover, model fit indices for the cross-validation sample indicated a moderate to good fit with the data, $\chi^2 = 154.40; df = 50; p < .0000; CFI = 0.96; NNFI = 0.95; GFI = 0.96; AGFI = 0.90; RMSEA = 0.08, CI90 = 0.06, 0.09; RMR = 0.05, and SRMR = 0.05$. These statistics were within the acceptable range of a moderate fit for the model (Hair et al., 2006; Kline, 2011). The critical $N$ for this analysis was 175, which was less than the sample size of 350 used in the model estimation.

The global fit indices for the total analytical sample suggested that the model fit the data well, $\chi^2 = 119.46; df = 50; p < .0000; CFI = 0.99; NNFI = 0.98; GFI = 0.97; AGFI = 0.95; RMSEA = 0.04, CI90 = 0.03, 0.05; RMR = 0.03, and SRMR = 0.03$. These values were within acceptable good model fit guidelines (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Brown, 2006; Hu and Bentler, 1999; Kline, 2011). The critical $N$ for this analysis was 448, which was less than the sample size of 697 used in the model estimation.
Overall, the examination of the goodness-of-fit indices for the total analytical sample suggests that the 3-factor model solution fit the data well. Inspection of the standardized residuals and modification indices did not indicate any issues that needed further attention. The factor loading estimates showed that the scales were associated with the purported latent variables ($R^2$s ranged from 0.45 to 0.92), which support the theoretical basis for loading each item on each latent variable. Consequently, all 12 items as indicators of the three latent constructs appear to possess acceptable construct validity.

Table 4.10

*Measurement Model Global Fit Indices for Cross-Validation and Total Analytical Samples*

<table>
<thead>
<tr>
<th>Goodness-of-Fit Indices</th>
<th>CFA Models</th>
<th>Cross-Validation Random Sample ($n = 350$)</th>
<th>Total Analytical Sample ($n = 697; N = 180,711$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$</td>
<td></td>
<td>154.40</td>
<td>119.52</td>
</tr>
<tr>
<td>$df$</td>
<td></td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>df/Chi-Square</td>
<td></td>
<td>3.08</td>
<td>2.39</td>
</tr>
<tr>
<td>$p$ value</td>
<td></td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>GFI</td>
<td></td>
<td>0.93</td>
<td>0.97</td>
</tr>
<tr>
<td>AGFI</td>
<td></td>
<td>0.90</td>
<td>0.96</td>
</tr>
<tr>
<td>NFI</td>
<td></td>
<td>0.94</td>
<td>0.98</td>
</tr>
<tr>
<td>NNFI</td>
<td></td>
<td>0.95</td>
<td>0.98</td>
</tr>
<tr>
<td>CFI</td>
<td></td>
<td>0.96</td>
<td>0.99</td>
</tr>
<tr>
<td>IFI</td>
<td></td>
<td>0.96</td>
<td>0.99</td>
</tr>
<tr>
<td>RFI</td>
<td></td>
<td>0.93</td>
<td>0.97</td>
</tr>
<tr>
<td>RMSEA</td>
<td></td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>CI 90</td>
<td></td>
<td>0.06, 0.09</td>
<td>0.03, 0.05</td>
</tr>
<tr>
<td>RMR</td>
<td></td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>SRMR</td>
<td></td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Critical $N$</td>
<td></td>
<td>175</td>
<td>446</td>
</tr>
</tbody>
</table>

**Structural Model Global Fit Indices**

The researcher used SEM to examine the hypothesized structural relationships in LISREL 9.2. The structural model illustrated in Figure 4.2 was fitted to the polychoric correlation and asymptotic covariance matrices using the MLR estimation method. Based on
prior research and the SCT theoretical assumptions, Figure 4.2 illustrates that the three latent variables affected Algebra I achievement among ninth-grade African American male students across the United States. Specifically, the researcher hypothesized that self-efficacy, academic-engagement, and student-teacher relationships would positively predict variability in Algebra I achievement among study participants. The SEM estimation converged to an admissible 3-factor model solution (see Appendix B for the LISREL syntax).

![Figure 4.2. Structural model: Latent constructs and Algebra I achievement](image)

Table 4.11 includes the goodness-of-fit statistics for the structural model. The model yielded statistically significant Chi square, $-\chi^2 = 135.57; df = 59; p < .0000$. The fit indices were CFI = 0.99; NNFI = 0.98; GFI = 0.97; AGFI = 0.95; RMSEA = 0.04, CI$_{90}$ = 0.03, 0.05; RMR = 66.
0.03, and SRMR = 0.03, which were consistent with the acceptable range for a good model fit (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Brown, 2006; Hair et al., 2006; Hu & Bentler, 1999; Kline, 2011). The correlation and covariance matrices predicted by the structural model accounted for 97% of the total variation in the sample correlation and covariance matrices (GFI = 0.97), and the relative model fit over the independent model was approximately 99% over the independent model fit (CFI = 0.99). In addition to the goodness-of-fit statistics, the researcher generated the Q-Plot of the standardized residuals for the structural model in LISREL. The points in the Q-Plot fell along the diagonal line. Taken as a whole, the results detailed in Table 4.11 and the Q-Plot of the structural model standardized residuals suggest that the model fit the data well.

Table 4.11

**Structural Model Global Fit Indices for Total Analytical Sample**

<table>
<thead>
<tr>
<th>Goodness-of-Fit Indices</th>
<th>Total Analytical Sample (n = 697; N = 180,711)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$</td>
<td>135.57</td>
</tr>
<tr>
<td>df</td>
<td>59</td>
</tr>
<tr>
<td>df/Chi-Square</td>
<td>2.30</td>
</tr>
<tr>
<td>p value</td>
<td>0.00</td>
</tr>
<tr>
<td>GFI</td>
<td>0.97</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.95</td>
</tr>
<tr>
<td>NFI</td>
<td>0.97</td>
</tr>
<tr>
<td>NNFI</td>
<td>0.98</td>
</tr>
<tr>
<td>CFI</td>
<td>0.99</td>
</tr>
<tr>
<td>IFI</td>
<td>0.99</td>
</tr>
<tr>
<td>RFI</td>
<td>0.97</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.04</td>
</tr>
<tr>
<td>CI 90</td>
<td>0.03, 0.05</td>
</tr>
<tr>
<td>RMR</td>
<td>0.03</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.03</td>
</tr>
<tr>
<td>Critical N</td>
<td>452</td>
</tr>
</tbody>
</table>
Effects of the Latent Constructs on Algebra I Achievement

The goal of the current study was to determine the effects of self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement of ninth-grade African American male students across the United States. The standardized regression coefficients among the latent variables and Algebra I achievement for the hypothesized structural portion of the full model are illustrated in Figure 4.3. The specifications on the hypothesized model were for a direct path from self-efficacy, academic engagement, and student-teacher relationships to Algebra I achievement. By default, relationships among latent variables were specified to covary (see Figure 4.3).

![Figure 4.3. Structural model with standardized path coefficients and t-values. Note: The bolded values indicate significant relationships. Full model accounted for 8% variance.](image)

As illustrated in Figure 4.3, the effect of self-efficacy on Algebra I achievement was positive ($\beta = 0.23$, $t = 5.55$, $p < .001$, $R^2 = 0.05$), indicating that the self-efficacy latent variable
explained only 5% of the variance in the Algebra I scores, which is small in magnitude.

Similarly, the effect of the student-teacher relationships construct on Algebra I achievement was positive and statistically significant ($\beta = 0.10$, $t = 2.34$, $p < .05$, $R^2 = 0.01$). The student-teacher relationship latent variable explained only 1% of the variability in Algebra I achievement. The magnitude of this effect size was small. In contrast, the academic engagement construct had a non-significant negative effect on Algebra I achievement ($\beta = -0.03$, $t = -0.61$). Taken together, self-efficacy, the amount of time students devoted to their homework, and student-teacher relationships explained only 8% of the variance in the Algebra I achievement among African American males in the United States ($R^2 = 0.08$). The magnitude of effects of these factors on Algebra I achievement was minimal.

Given the adequacy of the model, for each $SD$ change in the self-efficacy latent variable, Algebra I achievement should increase by 0.23 $SD$, and one $SD$ increase in the student-teacher relationships construct should increase Algebra I scores by 0.09 $SD$. Conversely, one $SD$ change in the academic engagement latent variable should decrease Algebra I achievement by 0.03 $SD$.

The researcher also examined other plausible relationships on the structural model to determine whether a significant correlation existed between self-efficacy and student-teacher relationships. Figure 4.3 shows a significant correlation between the constructs self-efficacy and student-teacher relationships ($r = 0.36$, $t = 9.89$, $p < .001$), which support the hypothesized relationship. The relationship between self-efficacy and academic engagement ($r = 0.04$; $t = 0.91$) and between academic engagement and student-teacher relationships ($r = 0.05$; $t = 1.25$) were positive but not statistically significant.

Examining the goodness-of-fit indices alone “does not ensure that the latent variables are substantively interrelated or account for meaningful variance in the indicators” (Brown 2006, p. 69).
Brown (2006) upheld that it is pivotal to evaluate parameter estimates to ascertain the acceptability of the model. To that end, the researcher generated and reviewed the standardized and unstandardized estimates for the observed indicators with their corresponding $t$-statistic values, error terms, and squared multiple correlations to determine their significance and magnitude in the model (see Table 4.12).

Table 4.12

*Structural Model LISREL Standardized and Unstandardized Estimates for the Total Analytical Sample (n=697; Weighted N=180,711)*

<table>
<thead>
<tr>
<th>Construct/Item</th>
<th>Standardized/Unstandardized $\lambda$ Estimates</th>
<th>$SE$</th>
<th>$t$-value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Self-Efficacy</td>
<td>Academic Engage</td>
<td>Student-Teacher $R$</td>
<td></td>
</tr>
<tr>
<td>Self-Efficacy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEFF2</td>
<td>0.87 (0.87)</td>
<td>0.01</td>
<td>64.68</td>
<td>0.75</td>
</tr>
<tr>
<td>MEFF3</td>
<td>0.72 (0.71)</td>
<td>0.02</td>
<td>34.68</td>
<td>0.52</td>
</tr>
<tr>
<td>MEFF4</td>
<td>0.78 (0.78)</td>
<td>0.02</td>
<td>44.23</td>
<td>0.61</td>
</tr>
<tr>
<td>MEFF5</td>
<td>0.86 (0.86)</td>
<td>0.01</td>
<td>63.27</td>
<td>0.74</td>
</tr>
<tr>
<td>Academic Engagement</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HWK1</td>
<td>0.72 (0.73)</td>
<td>0.03</td>
<td>25.80</td>
<td>0.52</td>
</tr>
<tr>
<td>HWK2</td>
<td>0.79 (0.77)</td>
<td>0.03</td>
<td>28.90</td>
<td>0.62</td>
</tr>
<tr>
<td>HWK3</td>
<td>0.67 (0.67)</td>
<td>0.03</td>
<td>23.47</td>
<td>0.45</td>
</tr>
<tr>
<td>Student-Teacher Relationships</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCR1</td>
<td>0.96 (0.95)</td>
<td>0.01</td>
<td>160.96</td>
<td>0.92</td>
</tr>
<tr>
<td>TCR2</td>
<td>0.89 (0.88)</td>
<td>0.01</td>
<td>96.93</td>
<td>0.80</td>
</tr>
<tr>
<td>TCR3</td>
<td>0.86 (0.86)</td>
<td>0.01</td>
<td>77.32</td>
<td>0.74</td>
</tr>
<tr>
<td>TCR4</td>
<td>0.79 (0.80)</td>
<td>0.02</td>
<td>51.66</td>
<td>0.63</td>
</tr>
<tr>
<td>TCR5</td>
<td>0.71 (0.73)</td>
<td>0.02</td>
<td>35.53</td>
<td>0.50</td>
</tr>
<tr>
<td>ALGEBRA I</td>
<td>0.23 (0.24)</td>
<td>-0.03 (-0.04)</td>
<td>0.10 (0.09)</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Note: Unstandardized coefficients are in parenthesis. All item coefficients are significant at $p<.000$, $n = 697$. Model fit indices $CFI = 0.99$, $GFI = 0.97$, $IFI = 0.99$, $RMSEA = .04$ (90% CI = 0.03 to 0.05).
The standardized and unstandardized results revealed that all items yielded regression coefficients above 0.50. These results indicate that all estimates were significant ($p < .000$) and exhibited moderate to large effect sizes that ranged from 0.45 to 0.92. The best measures for the self-efficacy latent variable were students’ confidence that they could master math skills ($\beta = 0.87, R^2 = 0.75$) and their confidence that they could understand the math textbook ($\beta = 0.86, R^2 = 0.74$). Students’ confidence in tackling math assignments ($\beta = 0.72, R^2 = 0.52$) and tests ($\beta = 0.78, R^2 = 0.61$) were moderate measures of self-efficacy. Coincidently, these two items had the highest factor loadings in the EFA analyses.

The amount of time students devoted to other homework or to studying during a typical school day was the best measure of the academic engagement construct ($\beta = 0.79, R^2 = 0.62$). The amount of time devoted to math homework was a moderate measure of the academic engagement construct ($\beta = 0.72, R^2 = 0.52$). Conversely, the amount of time devoted to science homework and to studying during a typical school day had the smallest regression coefficients ($\beta = 0.67$), and explained the least amount of variance ($R^2 = 0.45$).

Three items in the student-teacher relationships construct were strong measures. Teachers treating students with respect had the largest regression coefficient ($\beta = 0.96$) and accounted for the most variance ($R^2 = 0.92$). Teachers treating students fairly had a high coefficient ($\beta = 0.89$) and explained 84% of variability. Likewise, teachers valuing students’ opinions had a high standardized estimate ($\beta = 0.86$) and accounted for 74% of variance. The other two items, ninth graders’ fall 2009 math teachers think all students can be successful and ninth graders’ fall 2009 math teachers think mistakes are okay if students learn, moderately measured the construct. These two items accounted for 63% and 50% of the variance, respectively.
Summary

This chapter included a discussion of the EFA and CFA results as they related to reliability and validity of the study latent variables and the observed items. Additionally, the chapter included the results of SEM analyses conducted to answer the three research questions that guided the study. Chapter 5 includes a summary of the study, a discussion of the findings, and the implications for future research.
The goal of the current study was to discern the effects of ninth-grade African American male students’ math self-efficacy, academic engagement, and student-teacher relationships on Algebra I achievement using Bandura’s (1986) social cognitive theory (SCT) as a theoretical framework. To that end, a conceptual model of these three latent variables that affect math was specified and tested using structural equation modeling (SEM) and a nationally representative sample of African American males who were enrolled in ninth grade in fall 2009. The researcher conducted the following analyses: (a) exploratory factor analysis (EFA), (b) confirmatory factor analysis (CFA), and (c) SEM. The researcher conducted the EFA and CFA using a cross-validation technique (Byrne et al., 1989). This chapter includes a summary of the findings, the results, conclusions, limitations and delimitations, and recommendations for future research.

Summary of Findings

The EFA analyses revealed that the 12 study items significantly loaded on the three factors of self-efficacy, academic engagement, and student-teacher relationships. All three factors accounted for 72.8% of the total variance extracted. Examination of the scree plot revealed that the 12 items purportedly measured the three constructs.

The CFA model fitted to the cross-validation sample yielded moderate goodness-of-fit indices (Hair et al., 2006; Kline, 2011). The total analytical sample CFA yielded adequate model fit statistics (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Brown, 2006; Hair et al., 2006; Hu & Bentler, 1999; Kline, 2011). Moreover, the reliability and validity analyses revealed that
the study constructs had acceptable reliability (Fornell & Larcker, 1981; Nunnally, 1978) and validity (Fornell & Larcker, 1981; Hair et al., 2006).

The SEM model global indices met good model fit specifications (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988; Hu & Bentler, 1999). The self-efficacy and student-teacher relationships latent variables were significant predictors of Algebra I achievement and accounted for small effect sizes of 5% and 1% of the variability, respectively. Academic engagement was not a significant predictor of Algebra I. These latent variables not only had direct effects on Algebra I achievement, but they also affected Algebra I achievement by influencing other factors in the model. The full SEM model explained 8% variability in Algebra I achievement. The magnitude of the effect size was small; therefore, caution is advised in interpreting and generalizing these results.

Research Questions

Research Question 1

Research Question 1 was, “Is self-efficacy related to Algebra I achievement among ninth-grade African American male students across the United States?” The researcher hypothesized that math self-efficacy would have a positive effect on Algebra I achievement, as prior research has indicated that self-efficacy significantly affects math outcomes (Cordero et al., 2010; Fast et al., 2010; Marra et al., 2009). As hypothesized, the model discerned that self-efficacy had the strongest direct effect on Algebra I achievement. Furthermore, this latent variable had a significant indirect positive effect on Algebra I. These findings suggest that the self-efficacy latent variable not only has a direct influence on Algebra I achievement, but it also affects Algebra I achievement by influencing other factors in the model. For example, self-efficacy affects academic engagement, and in turn, academic engagement affects Algebra I scores.
Correspondingly, self-efficacy affects student-teacher relationship, and in turn, student-teacher relationships affect Algebra I. The direct effects of self-efficacy on Algebra I were consistent with both prior studies indicating that self-efficacy is related to student achievement (Cordero et al., 2010; Fast et al., 2010; Marra et al., 2009) and with Bandura’s (1986) SCT personal dimension. The personal dimension of SCT postulates that people’s beliefs about their capabilities affect the choices they make, their ambitious, the amount of effort they exert into a task, and their persistence (Bandura, 1991, 2000).

A cross-examination of the standardized coefficients revealed that participants’ confidence in mastering math skills, understanding math textbooks, and tackling assignments and assessments were significant measures of the self-efficacy latent construct. These measures exhibited high regression beta values with moderate to high effect sizes ($R^2$ ranged from 52% to 75%). These findings also support Bandura’s SCT personal dimension that asserts that self-efficacy is associated with the confidence people exhibit in different situations.

As noted in Chapter 4, for each $SD$ change in the self-efficacy latent variable, Algebra I achievement should increase by 0.23 $SD$. This result suggests that if schools implemented programs aimed to boost student morale, math self-efficacy would increase, and ultimately, student performance in Algebra I would improve. For example, implementing STEM camps coupled with mentoring programs where students are exposed to the vast opportunities in the field might also enhance their self-efficacy. An enhanced sense of self-efficacy could help students persist when faced with challenging circumstances (Bandura, 1986).

Research Question 2

Research Question 2 was, “Is academic engagement related to Algebra I achievement among ninth-grade African American male students across the United States?” The researcher
hypothesized that academic engagement would have a direct effect on Algebra I because previous research had shown that the amount of time students devote to doing homework and studying out of school during a typical day influences student outcomes (Cooper et al., 2006; Flowers & Flowers, 2008; Maltese et al., 2012; Strayhorn, 2010).

The findings did not support Research Question 2 directly. Rather, academic engagement had a negative direct effect on Algebra I. However, this latent variable also exerted a non-significant indirect effect on Algebra I scores. These findings suggest that the academic engagement construct not only had a negative direct influence on Algebra I achievement, but it also affected Algebra I achievement by influencing other factors in the model. For example, self-efficacy affects academic engagement, and in turn, academic engagement affects Algebra I scores. Additionally, student-teacher relationships affect academic engagement, and in turn, academic engagement affects Algebra I.

Although the academic engagement latent variable did not yield a positive direct effect as anticipated, it did yield indirect positive relationships, which support the behavioral dimension of SCT that postulates that people must believe they have the power to affect change by their actions (Bandura, 2005). Therefore, students have the power to attach different meanings to their homework assignments. As discussed in Chapter 4, one SD change in the academic engagement latent variable should decrease Algebra I achievement by 0.03 SD. With the help of stakeholders, these students could reverse this trajectory.

It is worth noting that 54% to 70% of participants spent less than an hour during a typical day doing homework or studying; therefore, they exhibited academic disengagement. Conversely, most participants responded that they had confidence to tackle math assignments. These findings pose an interesting paradox because one would expect that efficacious people
would devote more time to homework. A plausible relationship that emerged from the present study is that academic disengagement predicts low achievement. A possible reason for this paradox is that the issue of homework is contentious in the United States. Proponents of homework argue that more is beneficial and time spent on homework is an indicator of students investing time and effort into their studies (Gill & Schlossman, 2003). However, other researchers contend that time spent on homework is inversely related to student achievement and extensive homework does not motivate students to devote more time to their studies (Maltese et al., 2012; Trautwein, 2007).

A second possible reason for this paradox is that homework policies are not universal. It is also worth noting that some teachers do not attach consequences to failing to complete homework or to turning in late homework. For example, in most school districts in North Texas, students can turn in their work late and still get a passing grade. The lack of consistent homework policies has sent the wrong message to students; as a result, students may not take homework seriously. Further, academic disengagement may occur when the assigned homework is not challenging and students attach different meanings to it (Bempechat et al., 2011).

Finally, it is probable that most students spend a lot of their free time on their gadgets (e.g., video games, smartphones, television, etc.) or socializing with friends. Szymanski and Benus (n.d.) reported, “The video game industry is thriving even when most other aspects of the economy are struggling” (p. 4). They upheld that video gaming is a billion-plus dollar industry and that the vast majority (72%) of households play video games regularly. Research has established that the majority of teenagers spend enormous amount of time on video games and on social media. For example, Lenhart, Smith, Anderson, Duggan, and Perrin (2015) surveyed teens aged 13 to 17 and found that 52% of participants spent time playing video games with their
friends; 13% played video games daily. The authors also found that 79% of the teens exchanged
instant messages with their friends, and 27% did so daily. Most participants (72%) spent time
with their peers via social media with 23% doing so daily (Lenhart et al., 2015). With this
statistics, it is evident that teenagers nowadays devote less time to homework assignments and
studying outside of school in a typical day, and are therefore, academically disengaged.

Research Question 3

Research Question 3 was, “Are student-teacher relationships related to Algebra I
achievement among ninth-grade African American male students across the United States?” The
researcher assumed that student-teacher relationships would have a positive effect on Algebra I
as research has indicated that this latent variable influence student achievement (Chhuon &
Wallace, 2014; Cornelius-White, 2007; Hughes et al., 2008; Martin & Dawson, 2009). As
expected, the results revealed that the student-teacher relationships latent variable had a
significant direct effect on Algebra I achievement. Additionally, this variable had an indirect
effect on Algebra I. These findings suggest that student-teacher relationships not only directly
influenced Algebra I achievement but also influenced the other latent variables. Specifically,
student-teacher relationships affect self-efficacy, and in turn, self-efficacy affects Algebra I
achievement. Equally, student-teacher relationships affect academic engagement, and in turn,
academic engagement affects Algebra I achievement. The effects of student-teacher
relationships are consistent with prior studies that have shown students’ affective relationships
with their teachers influence academic outcomes (Chhuon & Wallace, 2014; Cornelius-White,
2007; Hughes et al., 2008; Martin & Dawson, 2009).

The current findings also suggest that teachers treating students with respect, fairly, and
listening to their opinions were best measures of the student-teacher relationships latent variable.
Evidently, students attach different meaning to a class when they know they are valued and their opinions matter. The findings also suggest that to foster student-teacher relationships, teachers must make an effort to engage or connect with students as recommended by McHugh et al. (2013). Teachers who forge relationships with their students show that they care about the students’ well-being and success as individuals. McHugh et al. upheld that teachers who stereotype students and do not pay attention demonstrate that they do not care about the students and are not interested in their academic success.

These results also support Bandura’s (1986) SCT environmental dimension, which stipulates that people have to be given environmental supports. This dimension also asserts that in any environment, people succeed because of the choices they make. If these students choose to establish and maintain meaningful relationships with their teachers, they will succeed academically. Equally significant, these results underscore the importance of affective relationships, as Bandura (1993) reported that affectionate processes influence self-efficacy.

Conclusion

Researchers have examined the effects of the self-efficacy (Cordero et al., 2010; Fast et al., 2010; Marra et al., 2009), academic engagement (Cooper et al., 2006; Flowers & Flowers, 2008; Maltese et al., 2012; Strayhorn, 2010), and student-teacher relationships (Chhuon & Wallace, 2014; Cornelius-White, 2007; Hughes et al., 2008; Martin & Dawson, 2009) latent variables on student achievement extensively. However, the majority of researchers have examined these constructs from a unidimensional perspective. Using Bandura’s (1986) theoretical framework, the researcher took a multi-faceted perspective to discern the influence of these constructs on Algebra I achievement among ninth-grade African American students across the United States using SEM analyses.
The results revealed that the measurement and structural models were adequate to discern the effects of the three constructs on Algebra I achievement among African American male students. The self-efficacy and student-teacher relationships latent variables emerged as significant predictors of Algebra I. Academic engagement was a negative non-significant predictor of Algebra I. Additionally, the results revealed that these latent variables indirectly influenced each other, and in turn, influenced Algebra I achievement. These findings suggest probable associations between the constructs; therefore, they should not be interpreted as causal relationships. Moreover, 25% of respondents had more than 15% missing data, and they were excluded from the analyses. Therefore, caution is advised in making generalization of these findings.

Regarding the theoretical framework, the self-efficacy results supported Bandura’s (1986) SCT personal dimension, which postulates that people’s beliefs about their capabilities affect the choices they make, their ambitious, the amount of effort they exert on a task, and their persistence (Bandura, 1991, 2000). The student-teacher relationships findings supported the environmental dimension of SCT, which stipulates that people have to be given environmental supports to thrive. Although the associations between self-efficacy and academic engagement, and between academic engagement and student-teacher relationships were not significant, they do suggest positive plausible relationships that support the assumption of SCT that human learning is an interaction between the individual, behavioral, and environmental constructs.

Limitations and Delimitations of the Study

This study had some of the same limitations that inherently affect the use of complex secondary data. For example, students’ responses were self-reported. Therefore, depending on when surveys were administered, varying conditions might have influenced responses. Equally
significant, the surveys were administered across the United States, and students from different regions might have interpreted the questions differently, especially given that the educational system is decentralized. Although Algebra I is considered a ninth-grade course; however, some students take the course in the eighth grade. Consequently, those students who take Algebra I in eighth grade might have forgotten some of the Algebraic reasoning concepts. These students might not have remembered everything when they took the Algebra I test as part of the HSLS:09 study.

Another limitation was that many data were incomplete and the researcher could not establish a reason for the missing data. Therefore, the findings are limited to participants who responded to the study items and the data the researcher successfully imputed using the FIML estimation method. Additionally, limited information was available to discern how much thought participants put into responding to the questionnaire. Therefore, the findings of the current study are only generalizable to 180,711 ninth-grade African American males who were enrolled in public schools across the United States in the fall of 2009.

Recommendations for Future Research

The researcher sought to determine the effects of three constructs on Algebra I achievement among ninth-grade African American male students enrolled in public schools. The research questions were answered using a conceptual model developed in lieu of an existing model. Therefore, the researcher recommends testing the developed model on another sample before generalizing the results. It would be ideal to determine whether the model and results hold for African American female students.

The researcher focused on students who were enrolled in public schools only; therefore, future studies should include male students enrolled in private schools. The researcher also
recommends replicating this study with other ethnic groups to examine similarities and differences between ethnic groups. A study across ethnic groups would entail conducting measurement invariance to discern whether the constructs have the same meaning for all ethnic groups studied.
REFERENCES


Appendix A

High School Longitudinal Study of 2009 (HSLS:09)

Student Questionnaire
* Questions marked with an asterisk (*) were not asked of all respondents.

SECTION A: Student Background

Next we are going to ask you a few questions about your background.

What is your sex?
  Male
  Female

Are you Hispanic or [Latino/Latina]?
  Yes
  No

* Which of the following are you?
  Mexican, Mexican-American, Chicano
  Cuban
  Dominican
  Puerto Rican
  Central American such as Guatemalan, Salvadoran, Nicaraguan, Costa Rican, Panamanian, or Honduran
  South American such as Colombian, Argentine, or Peruvian
  Other Hispanic or Latino or Latina

[In addition to learning about your Hispanic background, we would also like to know about your racial background.] Which of the following choices describe your race? You may choose more than one. (Check all that apply.)
  White
  Black or African American
  Asian
  Native Hawaiian or other Pacific Islander
  American Indian or Alaska Native

* Which one of the following are you?
  Chinese
  Filipino
  Southeast Asian such as Vietnamese or Thai
  South Asian such as Indian or Sri Lankan
  Other Asian such as Korean or Japanese

What is your birth date?
  Month
  Day
  Year
  1991 or earlier
  1992
1993
1994
1995
1996 or late

What was the first language you learned to speak when you were a child? Was it...
- English
- Spanish
- Another language
- English and Spanish equally or
- English and another language equally?

* What is the [other] language you first learned to speak?
  - A European language, such as French, German, or Russian
  - A Chinese language
  - A Filipino language
  - A Southeast Asian language such as Vietnamese or Thai
  - A South Asian language such as Hindi or Tamil
  - Another Asian language such as Japanese or Korean
  - A Middle Eastern language such as Arabic or Farsi, or
  - Another language

* How often do you speak [this language] with your mother or female guardian at home?
  - Never
  - Sometimes
  - About half the time
  - Most of the time
  - Always
  - No mother or female guardian in your household

* How often do you speak [this language] with your friends?
  - Never
  - Sometimes
  - About half the time
  - Most of the time
  - Always
SECTION B: Previous School Experiences

Next we are going to ask you a few questions about your background.

What grade were you in last school year (2008-2009)?
- 7th Grade
- 8th Grade
- 9th Grade
- You were in an ungraded program

During the last school year (2008-2009), did you attend [current school] or did you attend a different school?
- [current school]
- Different school
- You were homeschooled

* During the last school year (2008-2009), what school did you attend?
  - School Name
  - City
  - State/Foreign County

Since the beginning of the last school year (2008-2009), which of the following activities have you participated in?
(Check all that apply.)
- Math club
- Math competition
- Math camp
- Math study groups or a program where you were tutored in math
- Science club
- Science competition
- Science camp
- Science study groups or a program where you were tutored in science
- None of these

Since the beginning of the last school year (2008-2009), how often have you done the following science activities?
- Read science books and magazines
  - Never
  - Rarely
  - Sometimes
  - Often
- Accessed web sites for computer technology information
  - Never
  - Rarely
  - Sometimes
  - Often
- Visited a science museum, planetarium or environmental center
Never
Rarely
Sometimes
Often

* What math course did you take in the 8th grade? If you took more than one math course, please choose your most advanced or most difficult course.
  - Math 8
    - Advanced or Honors Math 8 not including Algebra
    - Pre-algebra
    - Algebra I including IA and IB
    - Algebra II or Trigonometry
    - Geometry
    - Integrated Math
    - Other advanced math course such as pre-calculus or calculus
    - Other math

* What was your final grade in this math course?
  (If your school uses numerical grades only, please answer in terms of the letter equivalent. If you don't know the equivalent, assume that ...
  - 90 to 100 is an "A"
  - 80 to 89 is a "B"
  - 70 to 79 is a "C"
  - 60 to 69 is a "D"
  - Anything less than 60 is "below D")
  - A
  - B
  - C
  - D
  - Below D
  - Your class was not graded

* What science course did you take in the 8th grade? If you took more than one science course, please choose your most advanced or most difficult course.
  - Science 8
    - General Science or General Science 8
    - Biology
    - Life science
    - Pre-AP or pre-IB Biology
    - Chemistry
    - Earth Science
    - Environmental Science
    - Integrated Science
    - Principles of Technology
    - Physical Science
    - Physics
    - Other science course
* What was your final grade in this science course?
(If your school uses numerical grades only, please answer in terms of the letter equivalent. If you don't know the equivalent, assume that ... 
90 to 100 is an "A"
80 to 89 is a "B"
70 to 79 is a "C"
60 to 69 is a "D"
Anything less than 60 is "below D")

A
B
C
D
Below D
Your class was not graded

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SECTION C: Math Experiences

Now we are going to ask you a few questions about your experiences with math.

How much do you agree or disagree with the following statements?

- You see yourself as a math person
  - Strongly agree
  - Agree
  - Disagree
  - Strongly disagree
- Others see you as a math person
  - Strongly agree
  - Agree
  - Disagree
  - Strongly disagree

When you are working on a math assignment, how often do you think you really understand the assignment?

- Never
- Rarely
- Sometimes
- Often

Are you currently taking a math course this fall?
[Were you taking a math course in the fall of 2009?]

- Yes
- No

* What math course(s) are you currently taking this fall?
[What math course(s) were you taking in the fall (2009)?]
(Check all that apply.)

- Algebra I including IA and IB
- Geometry
- Algebra II
- Trigonometry
- Review or Remedial Math including Basic, Business, Consumer, Functional or General math
- Integrated Math I
- Statistics or Probability
- Integrated Math II or above
- Pre-algebra
- Analytic Geometry
- Other advanced math course such as pre-calculus or calculus
- Other math course

* Why are you taking [fall 2009 math course]?
[If late December or later add: If you are no longer taking this course, think back to the fall when you answer this question and the questions that follow.]
(Check all that apply.)
You really enjoy math
You like to be challenged
You had no choice, it is a school requirement
The school counselor suggested you take it
Your parent(s) encouraged you to take it
A teacher encouraged you to take it
There were no other math courses offered
You will need it to get into college
You will need it to succeed in college
You will need it for your career
It was assigned to you
Some other reason
You don’t know why you are taking this course

* How much do you agree or disagree with the following statements about your [fall 2009 math course]?
You are enjoying this class very much
  Strongly agree
  Agree
  Disagree
  Strongly disagree
You think this class is a waste of your time
  Strongly agree
  Agree
  Disagree
  Strongly disagree
You think this class is boring
  Strongly agree
  Agree
  Disagree
  Strongly disagree

* How much do you agree or disagree with the following statements about the usefulness of your [fall 2009 math] course? What students learn in this course...
  is useful for everyday life.
    Strongly agree
    Agree
    Disagree
    Strongly disagree
  will be useful for college.
    Strongly agree
    Agree
    Disagree
    Strongly disagree
  will be useful for a future career.
    Strongly agree
    Agree

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Disagree
Strongly disagree
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
* How much do you agree or disagree with the following statements about your [fall 2009 math] course?
You are confident that you can do an excellent job on tests in this course
   Strongly agree
   Agree
   Disagree
   Strongly disagree
You are certain that you can understand the most difficult material presented in the textbook used in this course
   Strongly agree
   Agree
   Disagree
   Strongly disagree
You are certain that you can master the skills being taught in this course
   Strongly agree
   Agree
   Disagree
   Strongly disagree
You are confident that you can do an excellent job on assignments in this course
   Strongly agree
   Agree
   Disagree
   Strongly disagree
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
* How much do you agree or disagree with the following statements about [your math teacher]?
Remember, none of your teachers or your principal will see any of the answers you provide. Your math teacher...
values and listens to students’ ideas.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
treats students with respect.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
treats every student fairly.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
thinks every student can be successful.
   Strongly agree
   Agree
Disagree
Strongly disagree
thinks mistakes are okay as long as all students learn.
Strongly agree
Agree
Disagree
Strongly disagree
treats some kids better than other kids.
Strongly agree
Agree
Disagree
Strongly disagree
makes math interesting.
Strongly agree
Agree
Disagree
Strongly disagree
treats males and females differently.
Strongly agree
Agree
Disagree
Strongly disagree
makes math easy to understand.
Strongly agree
Agree
Disagree
Strongly disagree
SECTION D: Science Experiences

Now we are going to ask you a few questions about your experiences with science.

How much do you agree or disagree with the following statements?

- You see yourself as a science person
  - Strongly agree
  - Agree
  - Disagree
  - Strongly disagree
- Others see you as a science person
  - Strongly agree
  - Agree
  - Disagree
  - Strongly disagree

When you are working on a science assignment, how often do you think you really understand the assignment?

- Never
- Rarely
- Sometimes
- Often

Are you currently taking a science course this fall?
[Were you taking a science course in the fall of 2009?]
- Yes
- No

* What science course(s) are you currently taking this fall?
[What science course(s) were you taking in the fall (2009)?] (Check all that apply.)
- Biology I
- Earth Science
- Physical Science
- Environmental Science
- Physics I
- Integrated Science I
- Chemistry I
- Integrated Science II or above
- Anatomy or Physiology
- Advanced Biology such as Biology II, AP, or IB
- Advanced Chemistry such as Chemistry II, AP, or IB
- General Science
- Principles of Technology
- Life Science
- Advanced Physics such as Physics II, AP or IB
- Other earth or environmental sciences such as ecology, geology, oceanography, or
meteorology
Other biological sciences such as botany, marine biology, or zoology
Other physical sciences such as astronomy or electronics
Other science course

* Why are you taking [fall 2009 science course]?
[If late December or later add: If you are no longer taking this course, think back to the fall when you answer this question and the questions that follow.]
(Check all that apply.)
You really enjoy science
You like to be challenged
You had no choice, it is a school requirement
The school counselor suggested you take it
Your parent(s) encouraged you to take it
A teacher encouraged you to take it
There were no other science courses offered
You will need it to get into college
You will need it to succeed in college
You will need it for your career
It was assigned to you
Some other reason
You don’t know why you are taking this course

* How much do you agree or disagree with the following statements about your [fall 2009 science] course?
You are enjoying this class very much
Strongly agree
Agree
Disagree
Strongly disagree
You think this class is a waste of your time
Strongly agree
Agree
Disagree
Strongly disagree
You think this class is boring
Strongly agree
Agree
Disagree
Strongly disagree

* How much do you agree or disagree with the following statements about the usefulness of your [fall 2009 science] course? What students learn in this course...
is useful for everyday life.
Strongly agree
Agree
Disagree
Strongly disagree
will be useful for college.
Strongly agree
Agree
Disagree
Strongly disagree
will be useful for a future career.
Strongly agree
Agree
Disagree
Strongly disagree

* How much do you agree or disagree with the following statements about your [fall 2009 science] course?
You are confident that you can do an excellent job on tests in this course
Strongly agree
Agree
Disagree
Strongly disagree
You are certain you can understand the most difficult material presented in the textbook used in this course
Strongly agree
Agree
Disagree
Strongly disagree
You are certain you can master the skills being taught in this course
Strongly agree
Agree
Disagree
Strongly disagree
You are confident that you can do an excellent job on assignments in this course
Strongly agree
Agree
Disagree
Strongly disagree

* How much do you agree or disagree with the following statements about [your science teacher]?
Remember, none of your teachers or your principal will see any of the answers you provide. Your science teacher...
values and listens to students’ ideas.
Strongly agree
Agree
Disagree
Strongly disagree
treats students with respect.
Strongly agree
Agree
Disagree
Strongly disagree
treats every student fairly.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
thinks every student can be successful.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
thinks mistakes are okay as long as all students learn.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
treats some kids better than other kids.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
makes science interesting.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
treats males and females differently.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
makes science easy to understand.
   Strongly agree
   Agree
   Disagree
   Strongly disagree
SECTION E: Home and School

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Now we are going to ask you a few questions about your experiences at home and in school.

~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

How much do you agree or disagree with the following statements about your current school?

You feel safe at this school
   Strongly agree
   Agree
   Disagree
   Strongly disagree
You feel proud being part of this school
   Strongly agree
   Agree
   Disagree
   Strongly disagree
There are always teachers or other adults in your school that you can talk to if you have a problem
   Strongly agree
   Agree
   Disagree
   Strongly disagree
School is often a waste of time
   Strongly agree
   Agree
   Disagree
   Strongly disagree
Getting good grades in school is important to you
   Strongly agree
   Agree
   Disagree
   Strongly disagree

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How often do you...

go to class without your homework done?
   Never
   Rarely
   Sometimes
   Often
go to class without pencil or paper?
   Never
   Rarely
   Sometimes
   Often
go to class without books?
   Never
   Rarely
   Sometimes
   Often
go to class late?
Never
Rarely
Sometimes
Often

Not including lunch or study periods, what is your favorite school subject?
- English
- Foreign Language
- Science
- Art
- Music
- Mathematics
- Physical Education or Gym
- Religion
- Health Education
- Computer Education or Computer Science
- Social Studies, History, Government, or Civics
- Career preparation class such as health professions, business, or culinary arts
- Other

Not including lunch or study periods, what is your least favorite school subject?
- English
- Foreign Language
- Science
- Art
- Music
- Mathematics
- Physical Education or Gym
- Religion
- Health Education
- Computer Education or Computer Science
- Social Studies, History, Government, or Civics
- Career preparation class such as health professions, business, or culinary arts
- Other

How much do you agree or disagree with the following statements?
Studying in school rarely pays off later with good jobs
- Strongly agree
- Agree
- Disagree
- Strongly disagree
Even if you study, you will not be able to get into college
- Strongly agree
- Agree
- Disagree
- Strongly disagree
Even if you study, your family cannot afford to pay for you to attend college
Since the beginning of the last school year (2008-2009), which of the following people have you talked with about which math courses to take this year?

(Check all that apply.)
- Your mother or female guardian
- Your father or male guardian
- Your friends
- A favorite teacher
- A school counselor
- None of these people

Since the beginning of the last school year (2008-2009), which of the following people have you talked with about which science courses to take this year?

(Check all that apply.)
- Your mother or female guardian
- Your father or male guardian
- Your friends
- A favorite teacher
- A school counselor
- None of these people

Since the beginning of the last school year (2008-2009), which of the following people have you talked with about which courses to take this year other than math and science courses?

(Check all that apply.)
- Your mother or female guardian
- Your father or male guardian
- Your friends
- A favorite teacher
- A school counselor
- None of these people

Since the beginning of the last school year (2008-2009), which of the following people have you talked with about going to college?

(Check all that apply.)
- Your mother or female guardian
- Your father or male guardian
- Your friends
- A favorite teacher
- A school counselor
None of these people
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Since the beginning of the last school year (2008-2009), which of the following people have you talked with about possible jobs or careers when you are an adult?
(Check all that apply.)
   Your mother or female guardian
   Your father or male guardian
   Your friends
   A favorite teacher
   A school counselor
   None of these people
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Since the beginning of the last school year (2008-2009), which of the following people have you talked with about personal problems?
(Check all that apply.)
   Your mother or female guardian
   Your father or male guardian
   Your friends
   A favorite teacher
   A school counselor
   None of these people
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
As far as you know, are the following statements true or false for your closest friend? Your closest friend...
   gets good grades.
       True
       False
   is interested in school.
       True
       False
   attends classes regularly.
       True
       False
   plans to go to college.
       True
       False
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
How much do you agree or disagree with each of the following statements?
If you spend a lot of time and effort in your math and science classes...
   you won’t have enough time for hanging out with your friends.
       Strongly agree
       Agree
       Disagree
       Strongly disagree
   you won’t have enough time for extracurricular activities.
       Strongly agree
       Agree
       Disagree
Strongly disagree
you won't be popular.
Strongly agree
Agree
Disagree
Strongly disagree
people will make fun of you.
Strongly agree
Agree
Disagree
Strongly disagree

In general, how would you compare males and females in each of the following subjects?

<table>
<thead>
<tr>
<th>Subject</th>
<th>Females are much better</th>
<th>Females are somewhat better</th>
<th>Females and males are the same</th>
<th>Males are somewhat better</th>
<th>Males are much better</th>
</tr>
</thead>
<tbody>
<tr>
<td>English or language arts</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Math</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

During a typical weekday during the school year how many hours do you spend...
working on math homework and studying for math class?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
working on science homework and studying for science class?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
working on homework and studying for the rest of your classes?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
participating in extracurricular activities such as sports teams, clubs, band, student government?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
working for pay not including chores or jobs you do around your house?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
spending time with your family?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
hanging out or socializing with your friends?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
watching television or movies?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
playing video games?
Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours
chatting or surfing online?

Less than 1 hour
1 to 2 hours
2 to 3 hours
3 to 4 hours
4 to 5 hours
5 or more hours

Are you participating in any of the following programs?

Talent Search
Yes
No

Upward Bound
Yes
No

Gear Up
Yes
No

AVID (Advancement in Individual Determination)
Yes
No

MESA (Mathematics, Engineering, Science Achievement)
Yes
No

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SECTION F: Plans for Postsecondary Education

Now we are going to ask you a few questions about your plans for school and college as you progress through high school.

Including this year, how many years of math do you expect to take during high school?
- One year
- Two years
- Three years
- Four or more years

* What are the reasons you plan to take more math courses during high school?
  (Check all that apply.)
  - Taking more math courses is required to graduate
  - Your parents will want you to
  - Your teachers will want you to
  - Your school counselor will want you to
  - You are good at math
  - You will need more math courses for the type of career you want
  - Most students who are like you take a lot of math courses
  - You enjoy studying math
  - Taking more math courses will be useful for getting into college
  - Taking more math courses will be useful in college
  - Your friends are going to take more math courses
  - Some other reason
  - You don’t know why, you just probably will

* Do you plan to enroll in...
  - an Advanced Placement (AP) calculus course?
    - Yes
    - No
    - You haven't decided yet
    - You don't know what this is
  - an International Baccalaureate (IB) calculus course?
    - Yes
    - No
    - You haven't decided yet
    - You don't know what this is

Including this year, how many years of science do you expect to take during high school?
- One year
- Two years
- Three years
- Four or more years

* What are the reasons you plan to take more science courses during high school?
  (Check all that apply.)
Taking more science courses is required to graduate
Your parents will want you to
Your teachers will want you to
Your school counselor will want you to
You are good at science
You will need more science courses for the type of career you want
Most students who are like you take a lot of science courses
You enjoy studying science
Taking more science courses will be useful for getting into college
Taking more science courses will be useful in college
Your friends are going to take more science courses
Some other reason
You don’t know why, you just probably will

* Do you plan to enroll in...
an Advanced Placement (AP) science course?
  Yes
  No
  You haven't decided yet
  You don't know what this is
an International Baccalaureate (IB) science course?
  Yes
  No
  You haven't decided yet
  You don't know what this is

An "education plan" or a "career plan" is a series of activities and courses that you will need to complete in order to get into college or be successful in your future career.
Have you put together...
a combined education and career plan
an education plan only
a career plan only or
none of these?

* Who helped you put your [education and career/education/career] plan together?
(Check all that apply.)
A counselor
A teacher
Your parents
Someone else
No one

Have you taken or are you planning to take...
the PSAT?
  No
  Yes
  You haven't decided yet
  You don't know what this is
the SAT?
No
Yes
You haven't decided yet
You don't know what this is
American College Testing Service (ACT) test?
No
Yes
You haven't decided yet
You don't know what this is
an Advanced Placement (AP) test?
No
Yes
You haven't decided yet
You don't know what this is
a test for the International Baccalaureate (IB)?
No
Yes
You haven't decided yet
You don't know what this is

How sure are you that you will graduate from high school?
Very sure you'll graduate
You'll probably graduate
You probably won't graduate
Very sure you won't graduate

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SECTION G: Life After High School

Now we are going to ask you a few questions about your future life after high school. We understand that you may not have thought a lot about some of these questions or you may not have all of the information right now. If you are unsure about how to answer a question, please make your best guess. Your thoughts are very important to us.

As things stand now, how far in school do you think you will get?
- Less than high school
- High school diploma or GED
- Start but not complete an Associate's degree
- Complete an Associate's degree
- Start but not complete a Bachelor's degree
- Complete a Bachelor's degree
- Start but not complete a Master's degree
- Complete a Master's degree
- Start but not complete a Ph.D., M.D., law degree, or other high level professional degree
- Complete a Ph.D., M.D., law degree, or other high level professional degree
- Don't know

* How sure are you that you will go on to college to pursue a Bachelor's degree after you leave high school?
  - Very sure you'll go
  - You'll probably go
  - You probably won't go
  - Very sure you won't go

Whatever your plans, do you think you have the ability to complete a Bachelor's degree?
- Definitely
- Probably
- Probably not
- Definitely not

Would you be disappointed if you did not graduate from college with a Bachelor's degree by the time you are 30 years old?
- Yes
- No

What do you plan to do during your first year after high school?
(check all that apply.)
- Enroll in an Associate's degree program in a two-year community college or technical institute
- Enroll in a Bachelor's degree program in a college or university
- Obtain a license or certificate in a career field
- Attend a registered apprenticeship program
- Join the armed services
- Get a job
- Start a family

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Travel
Do volunteer or missionary work
Not sure what you want to do

* Are you more likely to attend a public or private 4-year college, or have you not thought about this yet?
  - Public
  - Private
  - Haven’t thought about this

* Are you more likely to attend an in-state or out of state 4-year college, or have you not thought about it yet?
  - In-state
  - Out of state
  - Haven’t thought about this

* Have you gotten information about the cost of tuition and mandatory fees at a specific [in-state public/out-of-state public/private] college?
  - Yes
  - No

* What is the cost of one year’s tuition and mandatory fees at that public 4-year college in your state?
  Include the cost of courses and required fees such as student activity fees and student health fees. Do not include optional expenses such as room and board.

* Is that tuition and mandatory fees only, or does that also include other fees such as room and board?
  - Tuition and mandatory fees only
  - Tuition, mandatory fees, and other fees

* What is the cost of one year’s tuition and mandatory fees at that private 4-year college?
  Include the cost of courses and required fees such as student activity fees and student health fees. Do not include optional expenses such as room and board.

* Is that tuition and mandatory fees only, or does that also include other fees such as room and board?
  - Tuition and mandatory fees only
  - Tuition, mandatory fees, and other fees

* What is the cost of one year’s tuition and mandatory fees at that out-of-state public 4-year college?
  Include the cost of courses and required fees such as student activity fees and student health fees. Do not include optional expenses such as room and board.

* Is that tuition and mandatory fees only, or does that also include other fees such as room and board?
  - Tuition and mandatory fees only
  - Tuition, mandatory fees, and other fees

* What is your best estimate of the cost of one year's tuition and mandatory fees at a public 4-year college in your state?
Include the cost of courses and required fees such as student activity fees and student health fees. Do not include optional expenses such as room and board.

* Is that tuition and mandatory fees only, or does that also include other fees such as room and board?
  - Tuition and mandatory fees only
  - Tuition, mandatory fees, and other fees

* How confident are you in the accuracy of your estimate of the cost of one year’s tuition and mandatory fees at a public 4-year college in your state? Are you...
  - very confident
  - somewhat confident or
  - not at all confident?

As things stand now, what is the job or occupation that you expect or plan to have at age 30?
  - You don’t know
  - No
  - Yes

* How much have you thought about this choice? Have you thought about it...
  - not at all
  - a little
  - somewhat or
  - a lot?

When you talk about your plans for the future, would you say you talk...
  - mostly to your parents
  - more to your parents than your friends
  - to your parents and your friends about the same
  - more to your friends than your parents
  - mostly to your friends or
  - you don’t talk to your parents or to your friends about your plans for the future?
Appendix B

LISREL SYNTAX
!PRELIS SYNTAX: Can be edited
!This file reads the HSLS09 data set

SY='I:\HSLS09\HSLS0971715FIML12.LSF'

FT = hsls_thresholds.txt MEFF2
FT MEFF3
FT MEFF4
FT MEFF5
FT TCR1
FT TCR2
FT TCR3
FT TCR4
FT TCR5
FT HWK1
FT HWK2
FT HWK3

WE W1STUDEN
OU MA=CM PM=hslsfiml.PCM ACM=hslsfiml.ACM ME=hslsfiml.ME

**************************************************************************
****
CFA STRUCTURAL MODEL FREE ESTIMATES
! THIS SYNTAX IS FOR CFA ESTIMATES FOR RANDOMLY SAMPLE CROSS-VALIDATION SAMPLE.

Observed Variables
MEFF2 MEFF3 MEFF4 MEFF5 TCR1 TCR2 TCR3 TCR4 TCR5 HWK1 HWK2 HWK3

Correlation Matrix from File hslsfimlc.PCM
Asymptotic Covariance Matrix from File hslsfimlc.ACM
Means from File hslsfimlc.ME

SAMPLE SIZE IS 350

LATENT VARIABLES
SELFEEF ACADENG STRELATE ALG1

EQUATIONS:
MEFF2 = SELFEEF
MEFF3 = SELFEEF
MEFF4 = SELFEEF
MEFF5 = SELFEEF
HWK1 = ACADENG
HWK2 = ACADENG
HWK3 = ACADENG
TCR1 = STRELATE
TCR2 = STRELATE
TCR3 = STRELATE
TCR4 = STRELATE
TCR5 = STRELATE

Let the errors of TCR4 and TCR5 covary

iterations>300
admissibility check=on
path diagram
LISREL Output: SS SC MI ND=3 FS EF ALL RO WP RS
End of Problem
Syntax.txt 9/7/2015

******************************************************************************
**
CFA STRUCTURAL MODEL FREE ESTIMATES
! THIS SYNTAX ESTIMATES THE CFA MODEL FOR THE TOTAL ANALYTICAL SAMPLE

Observed Variables
MEFF2 MEFF3 MEFF4 MEFF5 TCR1 TCR2 TCR3 TCR4 TCR5 HWK1 HWK2 HWK3

Correlation Matrix from File hslsfiml.PCM
Asymptotic Covariance Matrix from File hslsfiml.AC
Means from File hslsfiml.ME

SAMPLE SIZE IS 697

LATENT VARIABLES
SELFEFF ACADENG STRELATE ALG1

EQUATIONS:
MEFF2 = SELFEFF
MEFF3 = SELFEFF
MEFF4 = SELFEFF
MEFF5 = SELFEFF
HWK1 = ACADENG
HWK2 = ACADENG
HWK3 = ACADENG
TCR1 = STRELATE
TCR2 = STRELATE
TCR3 = STRELATE
TCR4 = STRELATE
TCR5 = STRELATE

Let the errors of TCR4 and TCR5 covary

iterations>300
admissibility check=on
path diagram
LISREL Output: SS SC MI ND=3 FS EF ALL RO WP RS
End of Problem

******************************************************************************
**
SEM STRUCTURAL MODEL
! THIS SYNTAX ESTIMATES THE SEM MODEL FOR TOTAL ANALYTICAL SAMPLE.

Observed Variables
MEFF2 MEFF3 MEFF4 MEFF5 TCR1 TCR2 TCR3 TCR4 TCR5 HWK1 HWK2 HWK3 MTSCORE

Correlation Matrix from File hslsfiml.PCM
Asymptotic Covariance Matrix from File hslsfiml.AC
Means from File hslsfiml.ME

SAMPLE SIZE IS 697

LATENT VARIABLES
SELFEFF ACADENG STRELATE ALG1

EQUATIONS:
MEFF2 = SELFEFF
MEFF3 = SELFEFF
MEFF4 = SELFEFF
MEFF5 = SELFEFF

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HWK1 = ACADENG
HWK2 = ACADENG
HWK3 = ACADENG
TCR1 = STRELATE
TCR2 = STRELATE
TCR3 = STRELATE
TCR4 = STRELATE
TCR5 = STRELATE

MTSCORE=SELFYPE ACADENG STRELATE

Let the errors of TCR4 and TCR5 covary

iterations>300
admissibility check=on
path diagram
LISREL Output: SS SC MI ND=3 FS EF RS ALL
End of Problem