The unique contributions of math and science motivation to STEM outcomes for high school students: A model comparison study

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Abstract

The most recent U.S. National Science Foundation report on women, minorities, and persons with disabilities in science and engineering (2015) shows that the well-known gender gap in STEM continues to persist and yet the urgent need for a STEM-educated workforce grows. Thus, research in the area of STEM achievement motivation is one avenue for potentially understanding and intervening in the gender gap. The present study contributes to this literature by: 1) investigating the relationships between grade 9 motivational subconstructs (e.g., identity with the subject matter, and interest in the subject matter) in relation to the larger construct of motivation within the specific domains of math and science; 2) testing whether those motivational variables are related to end of high school STEM outcomes, including STEM career aspirations, STEM course credits earned, and STEM GPA; and 3) testing whether the relationships between STEM motivation variables and STEM outcomes are moderated by gender (in other words, are relationships stronger or weaker for females compared to males?). Specifically, the High School Longitudinal Study 2009 (HSLS:09) waves 1, 2, and 3 were employed, which included a nationally representative sample of N = 21,444 high school students who were followed from grade 9 in fall 2009 to grade 12 in spring 2013. In addition to investigating these substantive research questions, the present study also compared model estimates from Maximum Likelihood (ML), Weighted Least Squares Minimum Variance (WLSMV), and Bayesian estimators of each of the structural equation models, with and without use of complex sample survey weights. The results indicated that STEM motivation subconstructs are measuring similar but distinct domain-specific constructs, and that these constructs generally do predict STEM outcomes. Importantly, these relationships were not moderated by gender. Results of the model comparisons showed that ML estimation was the most flexible for analyzing these complex survey data, with WLSMV estimation the second most flexible method, and Bayesian the least flexible method. Discussion of substantive and statistical results and recommendations are provided.

Keywords: motivation, STEM, high school, achievement, structural equation modeling, estimators, Bayesian

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Acknowledgments

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Chapter 1: Introduction

A recent report by the U.S. National Research Council (NRC, 2011) called for expanding the number of students who pursue degrees and careers in STEM fields, particularly for women and minorities, by focusing on increasing awareness, access, and achievement in STEM education across the K-12 grade levels. The same NRC (2011) report stated that STEM careers are essential drivers of the economy through innovation, and that many students in the United States are not prepared to fill these STEM careers. The U.S. is falling behind other countries in providing for a much-needed STEM educated workforce (NRC, 2011).

Along with the need to increase STEM participation overall, there is particular focus on increasing the participation of females in STEM. The most recent National Science Foundation report on women, minorities, and persons with disabilities in science and engineering (NSF; 2015) shows that the well-known underrepresentation of females in STEM fields is persisting in most, but not all, STEM disciplines. The NSF started tracking and reporting on the participation of these groups in 1993. This most recent report (2015) includes data from 1993 through 2012. Specifically, since 1993, the proportion of females receiving STEM degrees has risen, but has yet to reach the level of male participation. In 2012, females' participation remained below that of males' in engineering, computer sciences, mathematics and statistics, physics, and economics. Physics continues to have the lowest participation of females, averaging around 20% across all degree levels. Not all STEM fields have a disproportionate number of males however; in 2012, the proportion of females in the biosciences and social sciences ranged from between 49% and 58% (NSF, 2015). Despite research that shows that males and females do not differ in their aptitude for math and science (Hyde, Lindberg, Linn, Ellis, & Williams, 2008), females continue to be underrepresented in many STEM fields. According to Blickenstaff (2005), scientific inquiry can be improved by increasing the diversity of the people who do science because the

lenses a person brings to science affect not only the interpretation of results they obtain, but also the kinds of questions that are asked in the first place.

Much research has been conducted assuming a "pipeline model" in understanding the underrepresentation of females in STEM (e.g., Blickenstaff, 2005; Ing, 2014; Quinn & Cooc, 2015; Ma, 2011; Steffens, Jelenee, & Noack, 2010). Within this framework, the pipeline starts at interest in STEM in high school or earlier, and continues into a STEM college major and STEM degree, and ultimately ends in a STEM career. Any other non-STEM trajectory at any point along the path is considered "leaking from the pipeline" (Ma, 2011). Thus far, research shows that females leak from the STEM pipeline at every stage compared to males, resulting in a high degree of female underrepresentation in STEM occupations at the end of the pipeline (Ing, 2014; Ma, 2011; Steffens, Jelenee, & Noack, 2010). Interestingly, Ma's (2011) analysis of female persistence in the STEM pipeline found that females who expected to major in STEM fields were as persistent as males in attaining a STEM degree. However, not many females were inclined toward majoring in STEM fields when they were in high school: males were close to three times more likely than females to expect to go into a STEM college major. In other words, recruitment of females planning to major in STEM fields may be a key to increasing females' STEM degree attainment. This then raises the question: why don't more females expect to pursue a STEM major in the first place? In other words, what are the underlying motivations behind going into a STEM field?

In fact, general student enrollment in STEM coursework during high school has been the focus of many motivation research studies (e.g., Murphy, & Alexander, 2000; e.g. Britner, 2008; Eccles, & Wang, 2016; Nolen, 2003; Simpkins, & Davis-Kean, 2005; Velayutham, Aldridge, & Fraser, 2012). Although great emphasis is being placed on STEM education and motivation (see

for example: Flores, Navarro, Lee, & Luna, 2014; Heaverlo, Cooper, & Lannan, 2013; Valla, & Williams, 2012), recent studies of both males and females show that middle and high school students report increased boredom and decreased enjoyment of both math and science (Ahmed, van der Werf, Kuyper, & Minnaert, 2013; George, 2000; Gottfried, Fleming, & Gottfried, 2001; Hidi, 2000, Krapp, 2002). This mismatch between the need for more STEM-educated students, and high school students' lack of enrollment in STEM courses and majors, particularly for females, warrants further research so that we may: 1) better understand the link between students' psychological motivation constructs around STEM outcomes, and 2) from this information, infer how we might bolster STEM outcomes through improved educational experiences.

Purpose of the Study

Aim 1. The purpose of the present study is two-fold. First, I seek to understand and test relationships between U.S. high school students' 9th grade STEM motivation (as a major construct with subconstructs) and their 11th and 12th grade STEM-related outcomes using the frameworks presented in previous achievement motivation literature (Bandura, 1986, 1997; Collins, 2000; Carlone & Johnson, 2007; Eccles & Wang, 2016; Renninger & Hidi, 2016); additionally, I seek to investigate whether these relationships differ between males and females, or if they are "invariant" across genders[1].

Aim 2. The second aim of this study is to compare statistical approaches for evaluating the primary research question. In large-scale survey research, we often encounter complex

[1] The spirit of this dissertation it to test whether there is a gap for self-identified females compared to self-identified males. Thus, gender is defined in this study as a student's self-reported binary category of gender as either male or female; it does not necessarily reflect the student's sex or gender role identification (it depends on how the student interpreted the question), and as a binary variable, it necessarily omits students with non-binary gender orientations. Nevertheless, I acknowledge that gender is dynamic and fluid (Collins, 2000). Throughout this dissertation the words "male" and "female" have been used to denote students' self-reported sex and/or gender identification.

sampling designs, many patterns of missing data, and a variety of response types (i.e., continuous and categorical). As such, it is important to explore the available models and model estimation methods to understand best approaches to analyzing applied data. The present study will compare the performance of three estimation methods through M*plus* 7.4 in a structural equation model (SEM) with complex survey data: maximum likelihood estimation (ML), robust weighted least square estimation (WLSMV), and a Bayesian approach with non-informative priors. In addition, a variety of models will be specified for each type of estimation method.

My research questions are as follows.

1. For 9th grade U.S. high school students (across males and females):
    a. What are the relationships between psychological items and motivation subconstructs for each domain (math and science), including *identity*, *utility*, *self-efficacy*, and *interest*?
    b. What are the relationships between the motivation subconstructs (1a) and second-order *motivation* as a single construct for each domain (math and science)?
2. Do 9th grade math and science motivation factors each uniquely predict STEM outcomes, including: 11th grade STEM career aspirations, STEM-specific GPA by the end of high school, and total number of STEM credits earned during high school?
3. Are the relationships between math and science motivation and STEM outcomes different for males and females? In other words, is one kind of motivation more important than another for females compared with males?

4. Lastly, when data are analyzed using different estimation methods (ML, WLSMV, Bayesian), do these relationship estimates change, and how would these changes affect inferences?

Organization of this Dissertation

In Chapter 2, I provide an overview of the development of achievement motivation theory, from its early stages to common theories of today. Chapter 3 is a review of relevant literature on achievement motivation and male and female disparities in STEM. Chapter 4 offers an introduction on structural equation modeling, while Chapter 5 provides an overview of differences between the frequentist (traditional) statistical approach and the Bayesian approach. Chapter 6 describes the methods and analysis techniques used to test the research questions outlined above, and chapter seven provides the results of these analyses. Lastly, chapter eight summarizes the findings and offers recommendations for analysis techniques when analyzing complex survey data, and suggests avenues for future STEM intervention research.

Chapter 2: Development of Achievement Motivation Theories

The framing of the present study relies on theories of *motivation*. As Ryan and Deci (2000) noted "to be motivated means to be moved to do something" (p. 54). Put another way, motivation is "the physiological process involved in the direction, vigor, and persistence of behavior" (Bergin, Ford & Hess, 1993, p. 437, as cited in Murphy & Alexander, 2000, p. 28). Current theories of motivation stress the importance of beliefs, values, and goals, in explaining motivational outcomes such as persistence, vigor, quality, and performance, which is a marked change from early motivational theories that stressed the importance of drives or stimulus-response relationships (Pintrich & Schunk, 1996; Weiner, 1990). The empirical study of motivation dates back to the emergence of the field of psychology and has been studied using the lenses of introspection, behaviorism, cognitive, and sociocultural theories. As theories emerged and changed over time, so too have research methods used to test them. Such methods have included introspection, experiments using animals, experiments using human subjects, correlational analyses using analysis of variance, regression, hierarchical linear models, and structural equation models, as well as a wide array of qualitative analysis methodologies.

Early Theories

Early theories of motivation were rooted in philosophy and conceptualized as theories of volition, will, and instincts (Pintrich & Schunk, 1996). Volition and will theories viewed motivation as the process of acting on or bringing to fruition a desire or purpose, whereas instinct theories viewed motivation as innate predispositions manifested in behavior (Pintrich & Schunk, 1996). Key motivation researchers of the time were Wundt, James, and Ach. These researchers relied on a methodology called introspection where subjects were given a stimulus, such as an image or a sound, and reported what they thought and felt. At the time, introspection was considered scientific, because the same stimulus, instructions, and environment were given to

each subject and then results recorded (Boring, 1953). As the field of psychology continued to seek to be recognized as an empirical science however, psychologists moved away from the method of introspection and towards more robust experimental methods. Introspection came to be seen as unreliable with results that could not be verified (Boring, 1953; Pintrich & Schunk, 1996).

From the 1940's to the 1960's behaviorism ruled the study of motivation and the field of psychology in general. Behaviorism was founded on the belief that scientific evidence must be observable. Using this reasoning, behaviorism employed a methodology of manipulating environmental stimuli in laboratory experiments and observing behavioral outcomes (Pintrich & Schunk, 1996). During the time of behaviorism, the study of motivation focused on determining the roots of behavior (Weiner, 1990). The two main theories in behaviorism were conditioning theories and drive theories. Conditioning theories (such as classical and operant conditioning) emphasized explaining behavior through the link between stimuli and responses (Pavlov's study using a bell to induce salivation in dogs is the iconic example of classical conditioning). Drive theories, on the other hand, stressed the importance of internal biological factors related to behavior. When an organism is depleted of an essential need such as hunger or thirst, a drive engages and the organism is motivated to meet that need (Hull, 1943; Pintrich & Schunk, 1996; Skinner, 1948; Spence, 1956).

Behaviorist theories understood motivation to be behavioral responses due to environmental stimuli. To be motivated therefore meant to be highly likely to engage in a behavior. The research methodology most often used during the time of behaviorism involved laboratory experiments using animals. Human behavior was considered too complex to study in such a way and therefore, animal behavior was used to generalize to human behavior. Motivation

psychologists were interested in understanding what induced a resting organism into activity (Weiner, 1990). For example, Siegel and Siegel (1949) conducted an experiment using rats to determine the effect of emotionality (arousal) on water intake (a state of activity). The authors used a control group of rats who were not exposed to the stimulus, and the experimental group who were exposed to 20-45 seconds of intermittent shock. Afterwards, the water intake of both the control and experimental rats were recorded. The experimental rats drank significantly more water after 2 hours than the control rats. According to behaviorist theories, the experimental rats could be considered to be motivated to drink water since they were more likely to engage in the behavior.

Towards the 1960's, behaviorism began to be questioned by emerging cognitive theorists. One criticism was that behaviorism equated motivation with learning. Behaviorism was unable to distinguish between motivation and learning because its only point of measurement was overt behavior. For example, Wischner (1947) conducted an experiment using rats to determine the effect of punishment on learning. Wischner separated 30 rats into three groups, non-shock, shock-wrong, and shock-right. The rats were placed in a maze with two alleys, a "correct" lighted alley, and an "incorrect" darkened alley. The non-shock rats were given food for choosing the lighted alley, and nothing for the darkened alley. The shock-wrong rats were given food in the lighted alley and shocked in the darkened alley. The shock-right rats were given both food and a shock in the lighted alley and nothing in the darkened alley. Results showed that over multiple trials, the shock-wrong rats had the most correct responses, the no-shock rats had the second most correct responses, and the shock-right rats had the least amount of correct responses. Recalling that behaviorist theories considered motivation to be increased likelihood to engage in a behavior, the shock-wrong rats would be defined as the most motivated to choose the

lighted alley, however they are equally defined as learning the best. Here motivation and learning are both being defined as frequency of choosing the correct alley. This experiment exemplifies the limitations of behaviorism as a means to study motivation. As the cognitive theorists pointed out, behaviorism could not distinguish between motivation and learning.

Although behaviorism is no longer the prevailing achievement motivation theory for typically developing children, behaviorist principles such as reward and punishment can still be seen in schools today with practices such as praise, time out, and token/point systems (Pintrich & Schunk, 1996). Reward and punishment do motivate behavior, however motivation is also dependent upon beliefs. Students are motivated to participate in activities that they *believe* will be rewarded and unmotivated to participate in activities that they *believe* will be punished. Similarly, research shows that when reward is perceived as controlling, it can be counterproductive, whereas when reward is perceived as positive feedback, it can be motivating. Reward can have different motivational consequences based on how it is perceived (Deci, 1975). Behaviorism was insufficient to account for the complexity of human motivation (Pintrich & Schunk, 1996; Weiner, 1990).

Cognitive Theories

By the 1960's, cognitive theories were gaining traction. Whereas behaviorism purposefully rejected looking inside the "black box" of the mind, cognitive theories sought to look inside the mind and understand the internal mechanisms for motivation. Cognitive theories date back to Tolman's research in the 1930's. Tolman, although a behaviorist, considered underlying mechanisms to behavior, stressing that behaviors are goal oriented, and must be interpreted as such (Pintrich & Schunk, 1996). Cognitive theorists moved away from studying animal behavior to studying humans. While cognitive theorists rejected many notions of

behaviorism, they did continue to attempt to isolate the determinants of behavior, using cognitive mechanisms as their unit of analysis (Weiner, 1990).

By the 1970's the study of motivation was firmly in the realm of educational psychology. Motivation research was dominated by the study of achievement motivation. Achievement motivation can be defined as "motivation in situations in which individuals' competence is at issue" (Wigfield & Eccles, 2002, p. 1). This shift to studying the interplay of motivation and competence was critical for the educational psychologist interested in student performance in the classroom, and would not have been possible with a psychology based on animal behavior (Weiner, 1990). Researchers often employed a 2x2 analysis of variance (ANOVA) design where, individuals were classified as high or low on a motivation related construct, such as achievement needs, anxiety, or locus of control, and outcomes such as choice and persistence were measured (Weiner, 1990). For example, Feather (1968) assessed undergraduate psychology students on their perceived locus of control. Students were divided into two groups, high in external control, meaning students view events as highly influenced by outside factors, and low on external control, meaning they view events as determined by their own behavior or ability. Students were further divided into two conditions: initial success, or initial failure. Students were given a 15-item anagram test, with the first 5 items being easy for the initial success group and the first 5 items being unsolvable for the initial failure group. Students rated their confidence before completing each anagram. Analysis of variance results showed that the internal control group changed their confidence ratings as a result of success or failure more than the external control group. Also, regardless of locus of control group, subsequent performance was lower in the initial failure group than the initial success group. The author concludes that initial success or failure may impact students' achievement motivation and in so doing, impact subsequent

performance. The use of the 2x2 ANOVA design resulted in a plethora of studies that categorized individuals as high or low on various constructs without much attention paid to variations within groups.

By the 1990's, cognitive theorists were continuing to focus on achievement motivation with increasing interest being paid to perceptions of the self as determinants of success or failure, with constructs such as: "self-actualization, self-concept, self-determination, self-esteem, self-focus, [and] self-handicapping" (Weiner, 1990, p. 621). Researchers continued to be interested in individual differences in achievement. With the advent of more powerful computers and more complex theories, researchers moved away from strictly 2x2 analysis of variance designs, to more complex models using regression, hierarchical linear modeling and structural equation modeling. Researchers also began to focus on achievement motivation within domain specific content (Weiner, 1990). For example, Bong (2001) used confirmatory factor analysis to study the relationships of self-efficacy, task-value, and achievement goals across the domains of Korean, English, math, and science among Korean students. Results indicated that students vary in their self-efficacy, task-value, and achievement goals, depending on the school subject or academic domain. For example, a student may be high in self-efficacy for math, but low in self-efficacy for science.

Sociocultural Theories

Beginning around 2000, sociocultural theories began to be brought to bear on achievement motivation research. In Nasir and Hand's (2006) overview of sociocultural theory, the authors state that sociocultural theory began in the 1900's with the work of Vygotsky. Sociocultural theory broadens the scope of analysis to include social and cultural processes that then mediate human behavior and cognitions. Sociocultural theorists stress that thought and

behavior do not exist in a vacuum, but are meaningfully influenced by social and cultural contexts (Bronfenbrenner, 1979). Nasir and Hand (2006) offer four core concepts in sociocultural theory, originally presented by Cole (1998), which are:

1. Development occurs on multiple levels simultaneously (moment-to-moment changes in learning and development; change over months and years; and change over historical and phylogenetic time).
2. Cultural practices are an important unit of analysis for understanding developmental processes.
3. Cultural tools and artifacts (including ideational or symbolic artifacts) fundamentally influence learning and development and are mediators of psychological processes.
4. Social others and social interactional processes play a key role in learning and development, and learning is constituted by changing relations in these social relationships and the social world (Nasir & Hand, 2006, pp. 458-459).

Sociocultural theories stress the interconnectedness between the individual and their environment. Much of the sociocultural achievement motivation research employs qualitative methodology. For example, Boaler and Greeno (2000) explored math identity by interviewing high school AP calculus students. The study consisted of 6 high school AP calculus classes. Two females and two males identified as mathematically confident and two females and two males identified as lacking confidence from each class were interviewed. In four of the AP calculus classes, students described a didactic classroom where students were expected to learn and replicate procedures taught by the teachers. In the other two AP calculus classes, students described a discussion-based environment where teachers explained methods to students, encouraged student discussion and students worked on problems in groups. In the two discussion based classes, students had many opportunities for self expression, identity development and knowledge construction through connected knowing. In contrast, in the didactic classes, the only identity available to students was that of a received knower where the students played a passive role in their learning (Boaler & Greeno, 2000). This example most closely highlights sociocultural core concepts two and four from the list above. In this example, the cultural

practices of the classroom are the unit of analysis and means for understanding student identity development. Also, the social interactions between the teacher and students is a key method for understanding how learning is taking place within the different classrooms.

Since the 1990's there has been a "growing presence and widening influence of motivation theory in educational research and practice" (Alexander, 2000, p. 1), which has led to a proliferation of motivation terms and constructs within the literature. In a special issue on Motivation and the Educational Process in the journal of Contemporary Educational Psychology, Murphy and Alexander (2000) conducted a literature review to identify key terms within the achievement motivation literature and document the different definitions used for these terms. The authors identified 68 articles that met their inclusion criteria, and found that over the span of five years, starting in 1992, the number of achievement motivation terms included per study almost doubled. They also found that while researchers often defined specific terms either explicitly or implicitly, they frequently neglected to define broad terms such as interest or motivation.

Today, motivation theories can be placed into two broad categories: 1) cognitive theories which focus on perceptions and the structure of thought (Weiner, 1990), and 2) sociocultural theories that stress the interconnectedness between the individual and their environment (Nasir & Hand, 2006). Current theories of motivation highlight beliefs, values, and goals as the primary motives for behavior. These theories are often complex and can include a mixture of environmental, cognitive, and social determinants (e.g. Bandura, 1986, 1997; Eccles & Wang, 2016; Esmonde, 2009; Hidi & Renninger, 2006; Simpkins, Davis-Kean, 2005; Solomon, 2007; Wenger, 1998). This is a departure from early theories of motivation which defined motivation in

terms of simpler stimulus-response processes. Table 1 highlights early theories of motivation and popular motivation theories of today.

Table 1.
Overview of Influential Motivation Theories

Early Theories	**Cognitive Theories**	**Sociocultural / Situative Theories**
Volition/Will (Ach, James, Wundt)	Social Cognitive Theory (Bandura)	Sociocultural Theory (Vygotsky, Esmonde, Wenger)
Behaviorism (Pavlov, Skinner)	Self-Determination Theory (Deci, Ryan)	Social Worlds (Holland)
Need Theories (Atkinson, Murray, Maslow, White)	Interest Theory (Hidi, Renninger, Krapp)	Distributed Cognition (Lave, Wenger)
	Attribution Theory (Weiner)	Situative Learning Theory (Greeno)
	Expectancy Value Theory (Wigfield, Eccles)	CHAT (Engestrom)

Chapter 3: Achievement Motivation in STEM

The purpose of this literature review is to examine the literature on the topic of motivation and STEM outcomes, in an attempt to demonstrate both a research and methodological gap that exists on the impact of key motivation subconstructs. This literature review will demonstrate that select motivation subconstructs are often analyzed but few studies have explored the collective influence of identity, utility, self-efficacy, and interest on STEM outcomes and whether these relationships are invariant across males and females. The review will also show that while many statistical methodologies are employed, few utilize advanced techniques such as Structural Equation Modeling (SEM) which is expressly designed to analyze underlying latent constructs. The unknown collective influence of identity, utility, self-efficacy, and interest on STEM outcomes for high school students and the limited use of advanced statistical models represent a gap in the literature.

Motivation Subconstructs and Male/Female Differences in STEM Outcomes

Much of the current achievement motivation research has been conducted within the domains of mathematics and science (Murphy & Alexander, 2000). Four key subconstructs of motivation have been shown to influence students' STEM outcomes and be moderated by gender: ***Identity*** (Cundiff, Vescio, Loken, & Lo, 2013; Inzlicht, & Schmader, 2012; Shih, Pittinsky, & Ambady, 1999; Walton, & Cohen, 2003), ***Utility*** (Eccles, & Wang, 2016; Simpkins, & Davis-Kean, 2005; Velayutham, Aldridge, & Fraser, 2012; Yang, & Barth, 2015), ***Self-Efficacy*** **(**Britner, 2008; Litzler, Samuelson, & Lorah, 2014), and ***Interest*** (Hidi, & Renninger, 2006; Renninger, & Hidi, 2011). The theoretical frameworks used in this study for each of the subconstructs are: Sociocultural Theory (Identity; Esmonde, 2009; Solomon, 2007; Wenger, 1998; Carlone & Johnson, 2007), Expectancy Value Theory (Utility; Eccles & Wang, 2016;

Simpkins, Davis-Kean, 2005), Self-Efficacy Theory (Self-efficacy; Bandura, 1986, 1997), and Interest Theory (Interest; Renninger & Hidi, 2016).

Self-efficacy.

Self-efficacy is defined as "people's judgements of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p.391). Self-efficacy is a subconstruct of Bandura's Social Cognitive Theory (SCT; 1986, 1997, 2001) which posits a cognitive model of motivation. An essential component of SCT is reciprocal determinism; a triadic model made up of Personal Determinants, Behavioral Determinants, and Environmental Determinants, in which individuals' actions are the result of the interactions between, personality characteristics, the individual's behavior, and external environmental factors (Bandura, 2012). Personal Determinants, of which self-efficacy is a part of, are characterized by cognition, affect, and biological events. Personal Determinants affect and are effected by Behavioral Determinants and Environmental Determinants. SCT posits that reciprocal determinism is the foundation for human behavior. Figure 1 shows that these relationships are bi-directional.

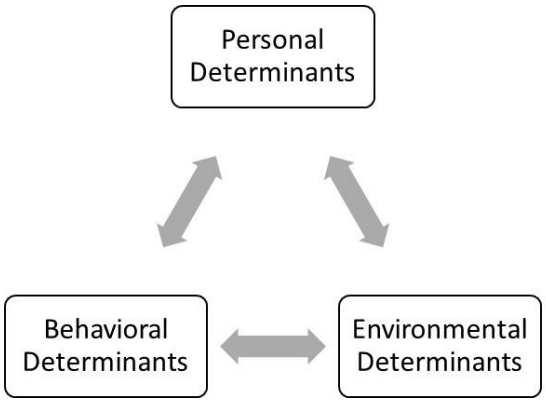


Figure 1. Schematization of Triadic Reciprocal Determinism in the Causal Model of Social Cognitive Theory (Bandura, 2012, p. 12).

Self-Efficacy theory is a component of the Personal Determinants portion of the SCT model. Research shows that there is a positive relationship between self-efficacy and achievement, (Britner, 2008; Chen, 2012; DiBenedetto, Bembenutty, 2013; Pajares, 1996;Williams & Williams, 2010; Zientek & Thompson, 2010) college major, (Pajares, 1996) and career choice (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Pajares, 1996). Research also shows that females report lower self-efficacy in STEM subjects than males, despite similar ability levels (Litzler, Samuelson, & Lorah, 2014; Pajares, 1996). However, current research shows that these findings no longer hold for all STEM fields, or all interactions between race/ethnicity and gender. For example, Britner (2008) studied science self-efficacy in high school science students, and found that females reported higher grades and higher self-efficacy in earth science classes than males, but in physical science classes, despite equal grades and equal reports of self-efficacy females still report higher science anxiety than male students. This finding is consistent with the data that show that the number of females equal or exceed the number of males in some STEM fields such as the biosciences and social sciences, however are still well below males in the physical science fields such as engineering and physics (NSF, 2015). These results show that self-efficacy is an integral and complicating subconstruct of motivation in STEM.

Interest.

The definition of interest used in this study comes from the work of Renninger and Hidi (2016), who state that interest is "the psychological state of a person while engaging with some type of content… and also the cognitive and affective motivational predisposition to reengage with that content over time"(p. 8). An interested person voluntarily engages in an activity and perseveres through challenges that arise (Renninger & Hidi, 2016). Hidi and Renninger (2006; Renninger & Hidi, 2016) describe a four-phase model of interest development which is made up

of triggered situational interest, maintained situational interest, emerging individual interest, and well developed individual interest (see Figure 2). Each motivational phase of interest corresponds to a psychological state. These phases and states are not different types of interest (as previously theorized), but different phases in the development of interest. An individual may progress, or regress through these phases due to environmental and personal characteristics (Renninger & Hidi, 2016).

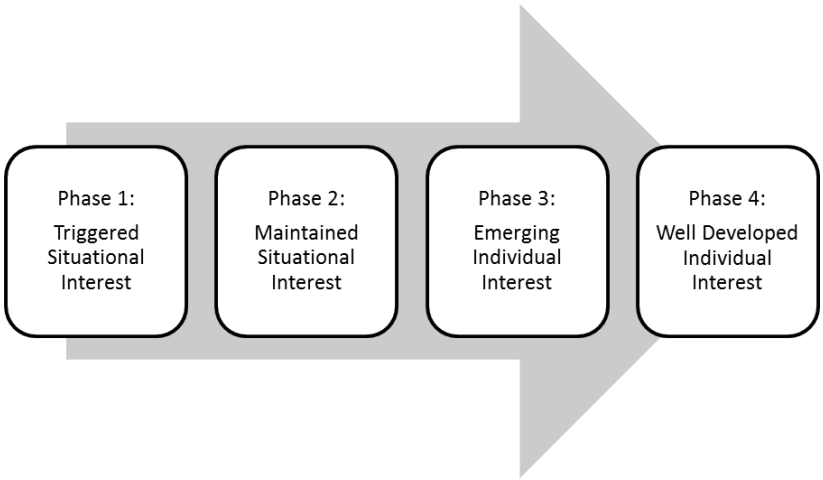


Figure 2. Four Phase Model of Interest Development

Research shows that there is a positive relationship between interest and achievement (Hoffman, 2002; Jansen, Ludtke, & Schroeders, 2016, Renninger & Hidi, 2011), and academic engagement (Patall, Vasquez, Steingut, Trimble, & Pituch, 2016, Renninger & Hidi, 2011), and that interest can be developed through tasks or the learning environment (Frenzel, Goetz, Pekrun, & Watt, 2010; Hoffmann, 2002; Renninger & Hidi, 2011). For example, Hoffman (2002) studied a physics curriculum intervention designed to increase females' interest in physics through curriculum oriented to contexts that both males and females could relate to for each unit, teacher-student interactions that lessoned gender specific interactions, and alternating coeducational and single sex teaching. Results showed that females in the intervention condition showed higher achievement and increased interest in physics than females in the control condition. This study

highlights that interest in a subject can be developed and that when gender bias in classroom environments is reduced, females' interest can increase.

Identity.

Contemporary sociocultural research on learning shows that learning and identity development are inextricably linked (Esmonde, 2009). Carlone & Johnson propose a model of identity composed of three dimensions: competence, performance, and recognition. The model illustrates that "one cannot pull off being a particular kind of person (enacting a particular identity) unless one makes visible to (performs for) others one's competence in relevant practices, and in response, others recognize one's performance as credible" (Carlone & Johnson, 2007, p. 1190). The model also asserts that one's gender, race and ethnicity are integral components in the construction of one's identity.

Much research demonstrates a link between identity and STEM outcomes (Cundiff, Vescio, Loken & Lo, 2013; Inzlicht & Schmader 2012; Steele 1997; Walton & Cohen, 2003); particularly with respect to the identity experiences of females in STEM courses and careers (Brickhouse, Lowery, & Schultz, 2000; Bruning, Bystydzienski, & Eisenhart, 2015; Carlone, & Johnson, 2007; Heyd-Metzuyanim, 2015; Hughes, 2015; Neumann, Lathem, & Fitzgerald-Riker, 2016). This research, predominantly qualitative, shows that females' experiences in STEM are nuanced and varied and their environments and interpersonal interactions have a direct impact on their identification with the discipline.

For example, Cundiff, Vescio, Loken, and Lo (2013) found that typical gender-science stereotypes were associated with weaker science identification and career aspirations for females, whereas males placed in the same typical gender-science stereotype condition showed stronger science identification and career aspirations. In another example, Carlone & Johnson (2007)

followed fifteen successful females of color throughout their higher education and into their science related careers. The authors found three science identity trajectories: research scientist, altruistic scientist, and disrupted scientist. Females in the research scientist identity trajectory recognized themselves and were recognized by others as "science people." This was performed for others and exemplified by choosing to work in a science lab, and engage in science "for science's sake." Females in the altruistic scientist identity trajectory were interested in science as a means to serve people by way of becoming doctors. These females did not seek or necessarily receive recognition from scientific others, but sought and received recognition from meaningful altruistic others. Lastly, females in the disrupted scientist identity trajectory encountered experiences where "they felt overlooked, neglected, or discriminated against by meaningful others within science" (p. 1202). This research shows the ways in which recognition of oneself and recognition of others is critical in identity development and impactful in STEM career choices. Based on theoretical and research support, identity can be distinguished as an integral motivational subconstruct in STEM academic outcomes and career aspirations.

Utility.

The expectancy value theory (EVT) of achievement motivation states that motivation and choices are related to subjective task values (STVs), which are "comprised of *interest value* (liking or enjoyment), *utility value* (the instrumental value of the tasks for helping to fulfill personal goals), *attainment value* (the link between the task and one's sense of self, identity, and core personal values), and *cost* (what may be given up by making a specific choice)" (Eccles & Wang, 2016, p. 100). Therefore, a person's choices such as course selection or college major are directly related to the value or utility the individual places on the choice options. The theory also states that choices are made within a social context and that utility beliefs can be influenced by broader societal constructs such as gender norms and roles (Eccles & Wang, 2016; Simpkins,

Davis-Kean, 2005). For example, Eccles and Wang (2016) found that male/female differences in the type of selected STEM career (health, biological, and medical versus mathematics, physical, engineering, and computer sciences) was related to male/female differences in value beliefs around people oriented versus thing oriented occupations. Similarly, Yang and Barth (2015) found that STEM students in biology and health majors were more people oriented than thing oriented and that females who enter STEM fields are more people oriented than thing oriented. Consistently, empirical research supports the theoretical claims that choices such as course selection, college major, and career selection are influenced by utility and value beliefs (Eccles & Wang, 2016; Simpkins, Davis-Kean, 2005; Velayutham, Aldridge, & Fraser, 2012; Yang and Barth, 2015).

Summary

Much of the research on motivation and male/female differences, has been conducted within the math and science disciplines. A search of the ERIC and PsycINFO databases using the terms: Achievement Motivation, Identity, Interest, Utility, Self-efficacy, STEM, Science, Technology, Engineering, Math, Gender, Gender-Gap and combinations of these terms, produced 58 empirical studies which were peer reviewed, contained at least one motivation subconstruct of interest, and included a study sample between 6^{th}-12^{th} grade or undergraduate students. The review is not meant to be comprehensive, but to provide an overview of current knowledge in the field. See Table 2 for a categorized list of the empirical motivation articles reviewed.

Table 2.
Coding of articles reviewed

Author(s)	*Date*	*Motivation Theory*	*Domain*	*Analysis Used*
Gaspard et al.	2015	EVT	Math	Multilevel Regression
Phan	2014	EVT	Math	SEM
Jacobs, Lanza, Osgood, Eccles, & Wigfield	2002	EVT	Math	HLM
Watt et al.	2012	EVT	Math	SEM
Priess-Groben & Hyde	2016	EVT	Math	SEM
Trautwein & Ludtke	2007	EVT	Math and Science	HLM
Eccles & Wang	2015	EVT	Math and Science	Regression
Eskreis-Winkler et al.	2016	EVT	Math and Science	Regression
Simpkins, Davis-Kean, & Eccles	2006	EVT	Math and Science	SEM
Andersen & Ward	2013	EVT	Math and Science	Regression
Denissen, Zarrett, & Eccles	2007	EVT	Math and Science	HLM
Simpkins, Davis-Kean	2005	EVT	Math and Science	Cluster analysis
Leaper, Farkas, & Brown	2012	EVT	Math and Science	Regression
Yang & Bath	2015	EVT	Math and Science	Repeated Measures ANOVA, Regression
Nagy, Trautwein, Baumert, Koller, Garrett	2006	EVT	Math and Science	SEM
Aschbacher, Ing, & Tsai	2014	EVT	Science	Latent class analysis
Cobb, Gresalfi, & Hodge	2009	Identity	Math	Qualitative
Nasir & Hand	2008	Identity	Math	Qualitative
Heyd-Metzuyanim	2015	Identity	Math	Qualitative
Esmonde	2009	Identity	Math	Qualitative
Hughes	2015	Identity	Math and Science	Qualitative
Carlone & Johnson	2007	Identity	Science	Qualitative
Barton et al.	2013	Identity	Science	Qualitative
Johnson, Brown, Carlone, & Cuevas	2011	Identity	Science	Qualitative
Hazari, Cass, & Beattie	2015	Identity	Science	Qualitative, and Regression
Brickhouse, Lowery, & Schultz	2000	Identity	Science	Qualitative
Tonso	1999	Identity	Science	Qualitative
Kane	2011	Identity	Science	Qualitative
Carlone, Scott, & Lowder	2014	Identity	Science	Qualitative
Stake & Nickens	2005	Identity	Science	Regression
Neumann, Lathem, & Fitzgerald-Riker	2016	Identity	Science	Qualitative
Frenzel, Goetz, Pekrun, & Watt	2010	Interest	Math	SEM
Jansen, Ludtke, & Schroeders	2016	Interest	Math and Science	Multilevel SEM
Chen et al.	2011	Interest	Math and Science	ANOVA
Hoffmann	2002	Interest	Science	Regression
Patall, Vasquez, Steingut, Trimble, & Pituch	2016	Interest	Science	HLM
Kim & Song	2009	Interest	Science	SEM
Usher	2009	Self-efficacy	Math	Qualitative
Zientek, & Thompson	2010	Self-efficacy	Math	Commonality Analysis
Williams, & Williams	2010	Self-efficacy	Math	SEM
Butz & Usher	2015	Self-efficacy	Math	Qualitative & Chi-Square tests
Jenson, Petri, Day Truman, & Duffy	2011	Self-efficacy	Math and Science	Qualitative
Wilson, Bates, Scott, Painter, & Shaffer	2015	Self-efficacy	Math and Science	T-tests
Britner	2008	Self-efficacy	Science	MANOVA, Regression
Chen	2012	Self-efficacy	Science	SEM
Chumbley, Haynes, & Stofer	2015	Self-efficacy	Science	Correlation
DiBenedetto & Bembenutty	2013	Self-efficacy	Science	Regression
Gonzalez & Paoloni	2015	EVT, SDT (self-determination theory)	Science	SEM
Bathgate, Schunn, Correnti	2013	Identity Interest EVT	Science	t-tests
Middleton	2013	Identity, Interest, Utility, Self-efficacy, Effort	Math	SEM with Weights
Cundiff, Vescio, Loken, & Lo	2013	Identity, Stereotype Threat	Science	Regression
Marsh, Trautwein, Ludtke, Koller, & Baumert	2005	Interest, Self-concept	Math	SEM
Nieswandt	2007	Interest, Self-concept	Science	SEM
Master, Cheryan, & Meltzoff	2016	Interest, stereotype threat	Science	ANOVA
hulleman et al.	2010	Interest/Utility	Math	Regression
Hulleman & Harackiewicz	2009	Interest/Utility	Science	Multiple Regression
Bong, Cho, Ahn, & Kim	2012	Self-efficacy, EVT	Math	SEM
Velayutham, Aldridge, & Fraser	2012	Utility, Self-efficacy	Science	SEM

Of the 58 empirical studies identified, 25 (43%) studied science fields only, 18 (31%) studied math fields only, and 15 (26%) studied math and science fields. Motivation research often focuses on a singular theory (n=47, 81%). The studies have also used a variety of analysis methods such as ANOVA, ANCOVA, MANOVA, Regression, HLM, SEM, and qualitative

methods. Few studies have used a SEM framework (n=14, 24%) to study the relationship between motivation and STEM outcomes and of these studies, many are from an expectancy-value theoretical perspective. Rarely are multiple motivation constructs measured from differing theories, and therefore not much is known about the relationships among constructs across theories (Bathgate, Schunn, & Correnti, 2013). An exception is a study by Middleton (2013) which investigated the relationship between interest, identity, utility, self-efficacy, and effort on math achievement, using the HSLS:09 dataset. Specifically, this study found that interest and effort are direct predictors of math achievement, with utility being indirectly related to math achievement through effort.

No study thus far, that I am aware of, has studied the relationship between four common cross-theory motivational subconstructs (interest, identity, utility, self-efficacy) across both math and science disciplines. It is important to study these constructs together, because there is the potential for significant overlap in their effects on STEM outcomes. For example, when an individual is deciding to enter a STEM discipline they most likely take into account each of the motivation subconstructs. Each of these subconstructs may mutually influence the other and contribute jointly to the decision of whether or not to enter a STEM discipline. Previous literature shows that each of these subconstructs predict STEM outcomes individually, but it's important to determine which ones, if any, provide additional explanatory power, or *uniquely* predict STEM outcomes. The current study seeks to add to the literature by analyzing the relationships among these subconstructs for math and science, their unique effects on STEM outcomes, and whether these relationships are invariant across males and females, using SEM methods.

Chapter 4: Structural Equation Modeling Methods

Overview

Structural equation models (SEMs) are a family of statistical procedures that employ an estimated covariance matrix to test hypotheses about relationships among exogenous (independent) and endogenous (dependent) variables. SEMs have also been called: covariance structure analysis, covariance structure modeling, and analysis of covariance structures to indicate this family of procedures (Kline, 2011). Three common procedures in the SEM family are path models, exploratory and confirmatory factor analyses (EFAs and CFAs, respectively), and more complex structural equation models (SEMs).

Path models are specified with observed variables only. Path models are similar to multiple regression and focus on mediation effects (causal chains) among multiple independent and dependent variables. Figure 3a is an example of a path model where, Y_2 is predicted by X_1 through the mediator variable Y_1. To add context, let's say that X_1 is student interest, Y_1 is student effort, and Y_2 is student achievement. Then, we have student achievement (Y_2) predicted by student interest (X_1) and mediated by student effort (Y_1). In other words, student interest predicts effort which then predicts achievement. In this example, student interest does not directly effect student achievement, it is only through student effort that interest predicts achievement.

The next set of models in the SEM family are EFAs and CFAs (Figure 3b). While an EFA tests the relationship between observed variables and one or more hypothesized latent variables, a CFA tests a constrained version of EFA. Latent variables are those that represent underlying constructs that we cannot observe directly. Motivation and intelligence are two examples of latent constructs. Observed variables that are used as indirect measures of latent

constructs are called indicators. For example, items on an I.Q. test are indicators of the latent construct intelligence. In EFA, we test the relationship (or "path" or "loading") between every observed variable (e.g., item responses from a survey) and every latent variable (e.g., motivation, or achievement), whereas in CFA we constrain certain paths to be zero (e.g., only the motivation survey items relate to the motivation latent construct, and only the achievement items relate to the achievement latent construct). The CFA is a simpler model compared to the EFA as it tests fewer paths, and if the model fit is not significantly worse in the CFA, then the CFA is said to be the best, most parsimonious model. In either case, both of these models are often called "measurement models" as they focus on the significance of relationships among observed items and latent variables.

Finally, complex SEMs tend to focus on the relationships *among the latent variables themselves*, often called the "structural" part of the model (Figure 3c). For example, the significance of the *relationship* among motivation and achievement may be of larger interest than the *measurement* of motivation and achievement constructs. In summary, when researchers refer to SEM, they are typically referring to models that focus on latent variable relationships (Schumacker & Lomax, 2010).

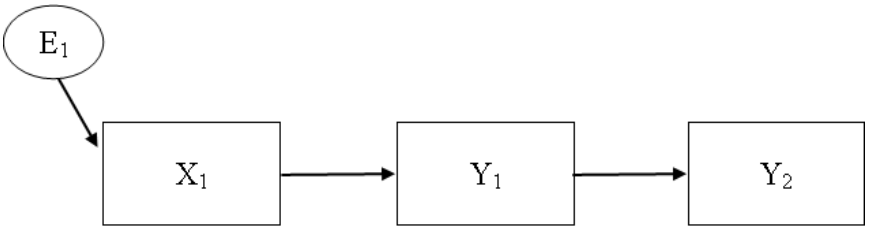
Specifics

Besides being able to estimate latent variables and their relationships, a major advantage to using SEM is the ability to model measurement error. Other estimation methods, such as traditional analysis of variance and multiple regression methods, assume perfect measurement of a construct. However, we know from classical test theory that scores comprise a true score from the latent construct and measurement error. SEM models assume measurement error and explicitly model it from the data.

All SEMs can be represented using a path diagram. The symbols used in path diagrams are: squares or rectangles for observed variables (e.g., □), circles or ellipses for latent variables (e.g., ○), a line with a single arrowhead for direct effects (e.g., →) and a line with two arrowheads for covariances and correlations that are not directional (e.g.,↔). The presence of a latent variable in a model implies, among other things, that the observed variables are free to have measurement error variance, and that these error variances are independent of each other. Further, a latent variable is theorized to *cause* the response we observe on measured variables, and so the arrow is purposefully directed from the latent variable to the observed variable(s).

Figure 3 provides an example of path diagrams for a path model (a), a confirmatory factor analysis (CFA) (b), and a structural equation model (SEM) (c). The Xs represent observed independent/predictor variables, the Ys represent observed dependent/outcome variables, the letters A and B represent latent (unobserved) variables, and Es represents error variance. Notice that the error terms are in ellipses, indicating that they too are latent variables. This is because error variance is not directly observable and therefore must be estimated using the whole model and the data (see for example Kline, 2011; Schumacker & Lomax, 2010). We can see in the path analysis model (a) that the path diagram only estimates two paths: the magnitude with which X_1 predicts Y_2, as mediated by Y_1. The CFA model (b) contains only a measurement model: just the path estimates to X_1, X_2, and X_3 from the single latent variable, A_1. Lastly, the SEM model (c) contains both a measurement component, which are the path estimates to X_1, X_2, and X_3 from the two latent factors A and B, and a structural component – which is usually of high interest – which in this model is the correlation estimated between the two latent factors, A and B.

(a)



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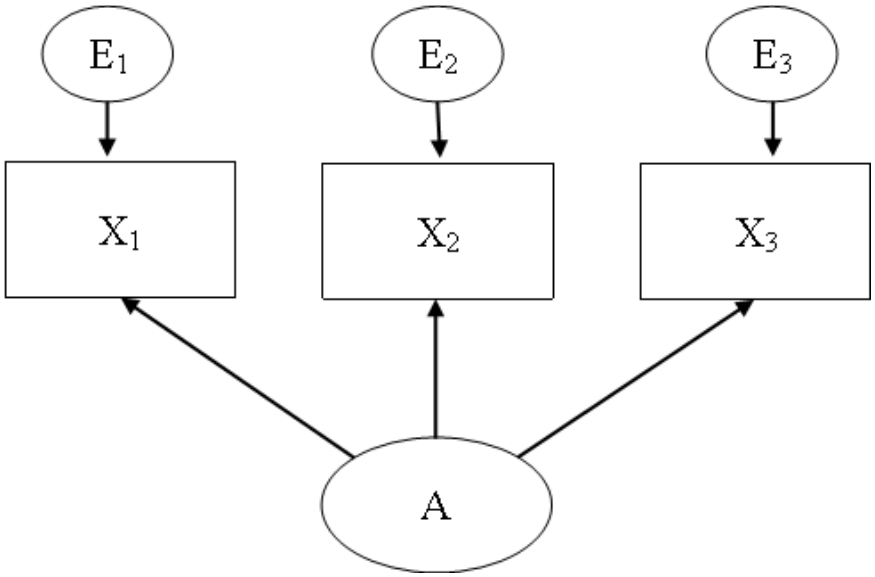

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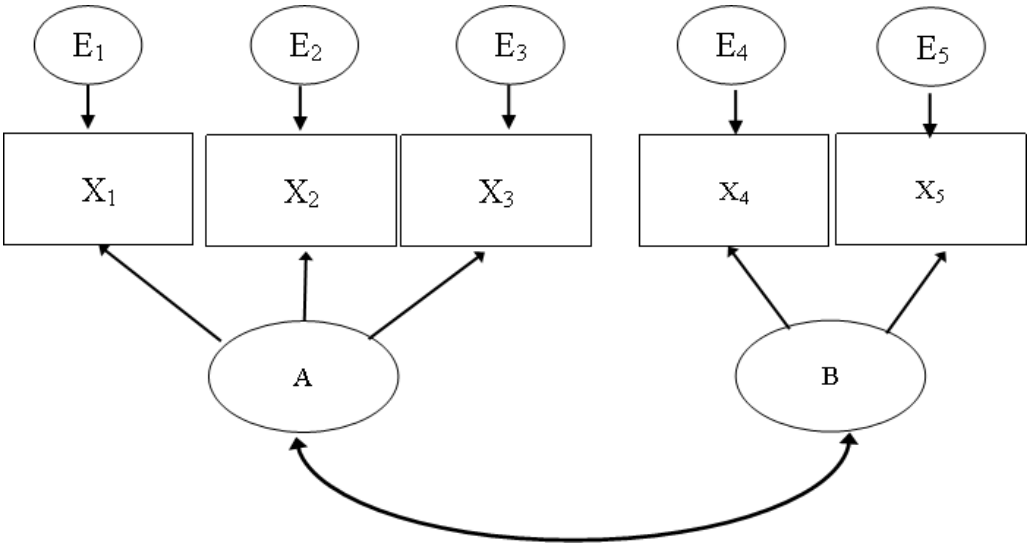


Figure 3. Examples of Path Diagrams for a Path Model, CFA, and SEM

As alluded to earlier, researchers are often interested in factor loadings, which are relationships between observed variables and latent constructs. These loadings can be thought of as similar to regression coefficients (Kline, 2011): in fact, not only is multiple regression a special case of SEM, but all GLM procedures are special cases of SEM (Bagozzi, Fornell, & Larcker, 1981; Fan, 1997; Graham, 2008). Graham (2008) shows how common GLM procedures can be represented and analyzed using a SEM framework. Using a multiple regression example adapted from Graham, we are interested in predicting the dependent variable Y_1 from independent variables X_1 and X_2. The GLM formula for this analysis is as follows.

$$\hat{Y}_i = b_0 + b_1 X_1 + b_2 X_2 + e_i$$

Where, $\hat{Y}_i$ is the estimated value of the i^{th} subject, holding all other variables constant, b_1 and b_2 are the slope of predictors X_1 and X_2 respectively (estimated average change in Y for each one unit increase in the predictor, holding all other variables constant), and e_i is the residual, unaccounted for, error for the i^{th} subject (the deviation between the observed Y and predicted $\hat{Y}$). Table 3 shows the multiple regression results from SPSS, where the independent variables accounted for 62% of the variance in the dependent variable.

Table 3.
SPSS Multiple Regression Anlaysis Results

Variable	*b*	*SE*	β	*t*	*P*	sr^2
X_1	0.790	0.036	0.819	22.131	<.001	0.623
X_2	0.319	0.054	0.219	5.918	<.001	0.045

Note. R^2= 0.623 [F (2,297)=244.89, p <0.001]

This multiple regression can also be expressed as a path diagram, shown in Figure 4. Notice there are no error terms associated with the independent variables in this diagram, because multiple regression assumes that independent variables are error free (an assumption that is almost always violated). The coefficients in the model are the standardized estimated results. The

loadings from the independent variable to the dependent variable are equivalent to the β weights from SPSS (0.819, 0.219). The coefficient on the double-headed arrow is the correlation between the two independent variables (-0.267). The coefficient for the error term associated with Y_1 is the percent of variance in Y not explained by X_1 and X_2 (0.377). Conversely, taking 1 – 0.377 provides the R^2 value of 0.623. For further examples of GLM procedures expressed in a SEM framework, including ANOVA and t-tests, see Graham (2008).

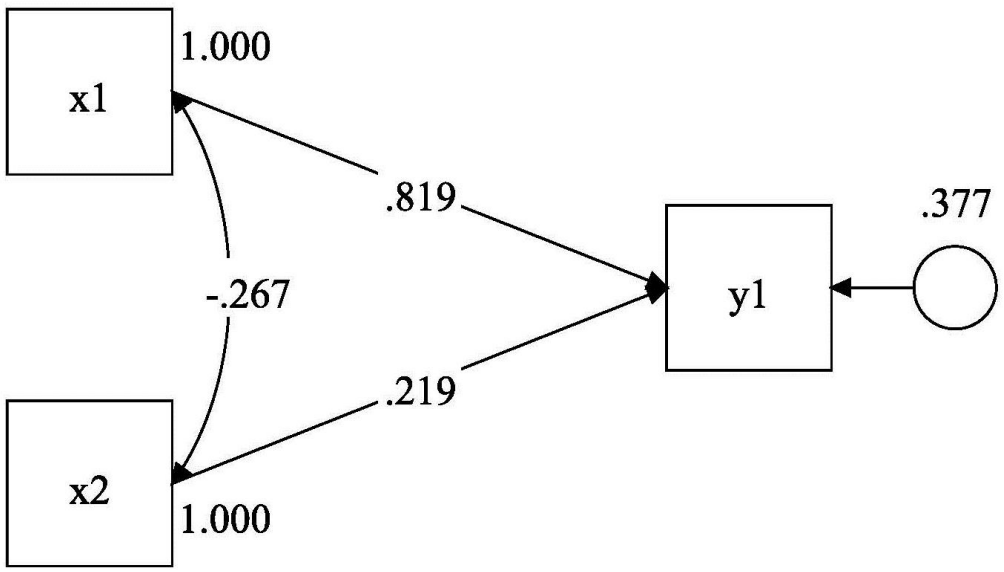


Figure 4. Multiple Regression Expressed as a Path Diagram

Finally, any SEM can be tested for invariance between groups. If a model is found to be invariant, it means that there are no significant differences between groups, say differences between males and females for example. Models can be tested at four hierarchical levels of invariance: configural, metric, scalar, and strict. Configural invariance tests whether the factor structure is the same across groups. For example, using Figure 4 above, we could say the model has configural invariance if both X_1 and X_2 predict Y_1 for both males and females. Metric invariance tests whether factor loadings are the same across groups. The model in Figure 4 could be said to have metric invariance if males and females both have a factor loading of .819

between X_1 and Y_1 and .219 between X_2 and Y_1. Scalar invariance tests whether factor loadings and factor intercepts are the same across groups. For example, males and females have the same intercept for Y_1. Lastly, strict invariance tests whether factor loadings, factor intercepts, and residual variances are the same across groups. For example, both males and females have a residual of .377 for Y_1 (Chen, 2007; Millsap, 2011; Sass, Schmitt, & Marsh, 2014).

This chapter served to provide a brief overview of SEM. There are many advantages to using SEM, including being able to test complex models which can include both observed and latent variables, the ability to specifically model error variance, and lastly, SEMs can be expanded to test group differences, hierarchical models, and longitudinal models. Although SEM provides great flexibility, some limitations should be mentioned. First, estimates of parameters, particularly standard errors in SEM, requires large sample sizes, compared to traditional univariate studies. The appropriate size will depend on the complexity of the model, but it is recommended to have sample sizes greater than 200 at the very least (Kline, 2011). A second limitation is the potential for confirmation bias. It is possible to have alternative models that explain the same pattern of observed covariances equally as well as the researcher's hypothesized model (Kline, 2011). It is important to test possible equivalent models to ensure there are not other explanations for the data. Although there are limitations, if these are kept in mind, SEM can be a powerful analytical tool.

Chapter 5: Overview of Bayesian vs. Frequentist Model Estimation Methods

Bayesian statistical methods are becoming increasingly more popular in the social sciences (Kruschke, 2015; Schoot et al., 2014; Zyphur & Oswald, 2015). This class of methods represents a fundamental paradigm shift in what is assumed of the random behavior of statistics and parameters. This chapter serves as an introduction to Bayesian methods with an emphasis on the differences between Bayesian and frequentist methods.

Frequentist Statistics

Frequentist methods represent the dominant methods in social science research, with traditional analyses such as *t*-tests, ANOVA, and regression (although the general ideas behind these hypothesis tests can be estimated from a Bayesian perspective as well). All frequentist methods employ probability theory to make inferences about the behavior of a sample statistic as being "rare" (i.e., significant) or "common" (i.e., not significant), regardless of the complexity of the model being studied. Frequentist methods associate probability with the frequency of an event over an infinite number of observations, or "in the long run." For example, frequentist probability states that the probability of a fair coin turning up heads is 0.50, because in the long run, or over an infinite number of coin flips, the coin lands heads half the time (Schoot et al., 2014; Zyphur & Oswald, 2015). For frequentists, parameters have true, fixed values that are estimated using statistics. These statistics are assumed to vary at random with a specific sampling distribution. Null hypothesis significance tests are shortcuts in determining whether the statistic, observed from a sample, is behaving in a rare or common fashion relative to its assumed sampling distribution (e.g., a 2-group *t*-test value is the distance between the group mean difference and zero in standard errors; this value can then be evaluated for its probability of occurring by chance). Estimated *p*-values are the probability of this statistic occurring by chance

(i.e., assuming that the null is true). If the *p*-value is sufficiently small enough ($p < 0.05$), we reject the null and state that there is evidence for a significant effect. Frequentists also often compute 95% confidence intervals to describe the level of uncertainty around a particular statistic and to indicate the values of a parameter that are likely given a statistic. These confidence intervals however, are often misunderstood. The correct interpretation is that over an infinite number of samples, the confidence interval will contain the parameter 95% of the time, *not* that there's a 95% probability that the interval contains the parameter.

Frequentist statistical theory, although the dominant viewpoint, has two limitations. Theoretically, it assumes that the parameters are constant and that the statistics vary around the parameters with some specific distribution (often normal/Gaussisan). In this way, previous information cannot necessarily be incorporated into current models because a specific distribution is assumed (Schoot et al., 2014; Zyphur & Oswald, 2015). On a more practical level, frequentist theory is limited in that it requires very large sample sizes to detect small effects for fairly simple models, as well as very large sample sizes to estimate very complex models (such as some SEMs). In fact, some models that can be estimated using a Bayesian approach are not estimable at all in the frequentist paradigm.

Bayesian Statistics

Bayesian and frequentist statistics are fundamentally different in how probability is conceptualized. Recall that frequentists associate probability with the frequency of an event over an infinite number of trials or samples; Bayesians associate probability with degrees of belief or knowledge (Zyphur & Oswald, 2015). Going back to the example of flipping a coin, the statement that a coin has a 0.50 probability of landing heads, for a Bayesian, means that there is no knowledge favoring heads over tails, or that belief is evenly divided between heads and tails

(Kruschke, 2015; Schoot et al., 2014; Zyphur & Oswald, 2015). This fundamental difference in the definition of probability changes the research question being asked. Using an example modified from Zyphur and Oswald (2015), linear regression can be used to determine the effect of peer tutoring (x) on achievement (y). The frequentist formula for this regression is:

$$y = \alpha + \beta x + \varepsilon$$

Where, β is the effect of peer tutoring. The frequentist research question becomes: given the null hypothesis, β=0 is true, how improbable is the effect of peer tutoring on achievement? Frequentists obtain a p-value using a sampling distribution, and if that p-value is less than .05 frequentists reject the null hypothesis that β=0. The Bayesian research question on the other hand is: Given prior and observed data, what is the probability distribution for β? After obtaining a probability distribution for β, the maximum of the distribution is used as the estimate for β and the uncertainty around that estimate is described using a 95% credibility interval. Bayesian statistics make direct inferences about parameters of interest; observed data are considered fixed and parameters are considered unknown and random reflected by a probability distribution.

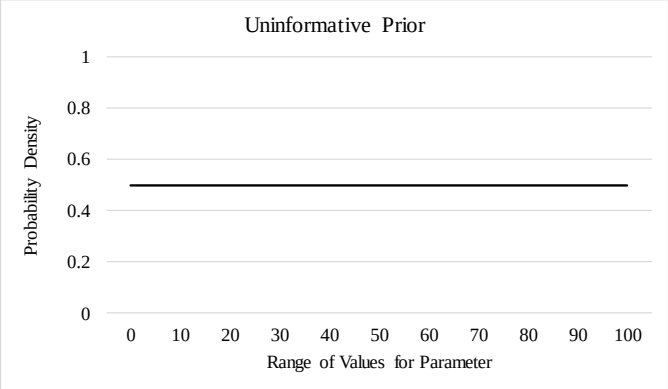
Three elements make up a Bayesian analysis. The first, is the prior distribution. The prior distribution can be informative or uninformative, but is always included. The second, is the likelihood function, which describes the observed data. Third, the prior distribution is combined with the likelihood function using Bayes' rule to produce the posterior distribution. Therefore, the posterior distribution is an updated version of the prior data based on the observed data (Kruschke, 2015; Schoot et al., 2014; Zyphur & Oswald, 2015).

Prior distribution.

The prior distribution is a key advantage to Bayesian statistics, because findings from previous research can be used to identify the prior distribution. The prior distribution reflects

how much knowledge we think we have before we've collected our observed data, and how precise we think that knowledge is (Schoot et al., 2013). In Bayesian analysis, a prior distribution is specified for every parameter in the model. Figure 5 shows examples of (a) uninformative (b) informative with high variance and (c) informative with low variance prior distributions. Figure 5a is uninformative, stating that all values are equally likely. Figure 5b is an example of an informative prior distribution, with a mean centered at 50, and a large variance. While Figure 5c is an example of an informative prior distribution with a mean of 50 and a small variance. The more precise a prior distribution, the more influence the prior distribution will have on the posterior distribution. In this way, Bayesian methods are intuitive: when we have a large amount of prior knowledge that we believe to be highly accurate, it will take a lot of conflicting data to change our beliefs (Kruschke, 2015).

(a)



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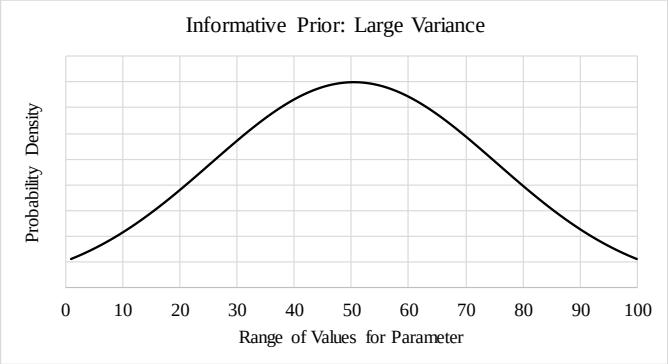

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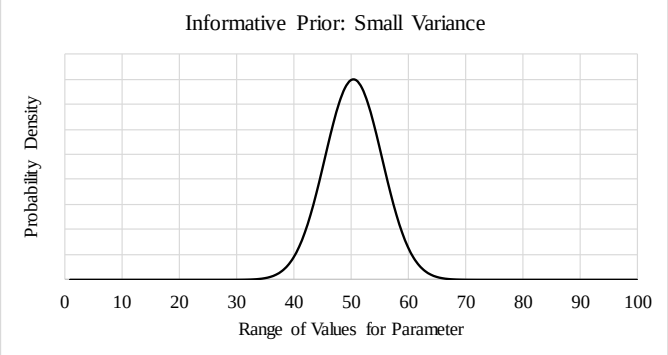


Figure 5. Examples of Prior Distributions

Likelihood function.

Once all prior distributions have been specified, the observed data can be analyzed. Parameters are summarized using the likelihood function. The likelihood function uses the observed data to compute the parameter values that are most likely (Schoot et al., 2013).

Posterior distribution.

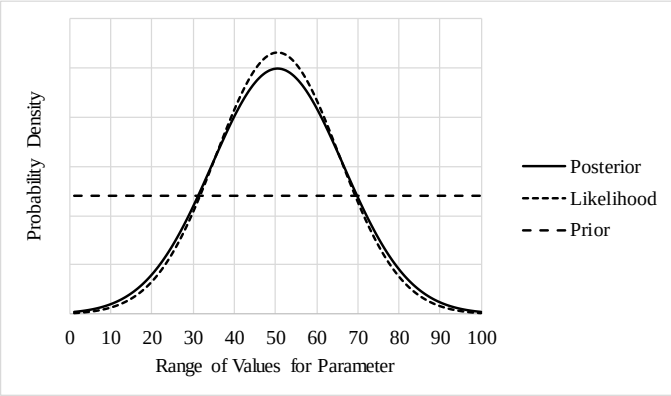
Lastly, the prior distribution and the likelihood are combined using the Bayes' rule to create the posterior distribution. The posterior distribution will always be a compromise between the prior distribution and the likelihood. Bayes' rule states:

$$\underbrace{P(\theta|D)}_{\text{Posterior Distribution}} \propto \underbrace{P(D|\theta)}_{\text{Likelihood}} * \underbrace{P(\theta)}_{\text{Prior Distribution}}$$

In words, the equation above states that the posterior probabilities of parameters given the data, P(θ|D) is proportional to the probability of the data given parameters θ, P(D|θ), multiplied by (weighted by) the probability of the prior parameters, P(θ). The posterior probabilities indicate how probable all parameter values are, given the data. They are proportional to: (a) the probability of the data given the range of possible parameters, P(D|θ), this is the information that observed data contribute during estimation, and (b) the prior probability distribution P(θ), which is the probability of all parameters prior to any data being collected (Zyphur & Oswald, 2015). Figure 6 shows two posterior distributions given an (a) uninformative and (b) informative prior and observed data. The figures show that when an uninformative prior is used, the posterior distribution will be similar to the likelihood. When an informative prior is used, the posterior distribution will be a compromise between the prior and the likelihood. The posterior distribution is created using Markov Chain Monte Carlo (MCMC) simulation methods. MCMC methods are

iterative. First, a prior distribution is specified. Then, “chains” of posterior parameter estimates are created over many iterations. Lastly, posterior values are estimated to build up and define the posterior distribution (Zyphur & Oswald, 2015). To ensure convergence of the estimates of the posterior parameters, at least two starting points are used to create two or more chains. This helps to ensure that a chain did not get stuck in the iteration process (Kruschke, 2015).

(a)



(b)

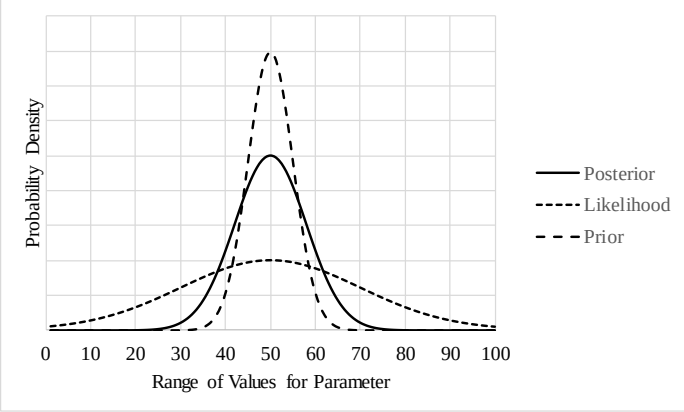


Figure 6. Posterior Distributions with Uninformative and Informative priors.

Lastly, once a posterior distribution is obtained, 95% credible intervals can be computed. These intervals are similar to the frequentist 95% confidence intervals, however they are much

more intuitive. A Bayesian 95% credible interval states that there is a 95% probability the parameter lies within the interval (Kruschke, 2015).

Summary

Table 4, adapted from Schoot et al. (2014), describes the differences between Bayesian and frequentist statistics. As described earlier, these differences start at the definition of probability and continue to the nature of parameters, the definition of uncertainty, estimated intervals, and the probabilistic conclusions that can be drawn from results. Studies show that regardless of the defined prior, as sample size increases, Bayesian and frequentist estimates will converge, however only Bayesian estimation allows for probabilistic statements about the parameters themselves (Schoot et al., 2014; Zyphur & Oswald, 2015).

Table 4.
Overview of the Differences Between Frequentist and Bayesian Statistics

	Frequentist Statistics	**Bayesian Statistics**
Definition of probability	Frequency over the long run	Degree of belief or knowledge
Nature of parameters	Unknown and fixed	Unknown and random
Where uncertainty lies	In the sampling distribution based on infinitely repeated sampling	In the probability distribution for the parameter
Estimated intervals	Confidence interval: Over an infinite number of samples, 95% of the intervals will contain the parameter	Credibility interval: There's a 95% probability that the parameter lies within the interval

Chapter 6: Methods

Dataset

Data collection.

The present study uses extant data from the High School Longitudinal Study of 2009 (HSLS:09), which is a federally sponsored longitudinal, nationally representative dataset. The study was designed, in part, to explore "the paths into and out of science, technology, engineering, and mathematics (STEM) fields of study and careers; and the educational and social experiences that are related to these shifts in plans or paths" (Ingels, Pratt, Herget, Burns, Dever, Ottem, Rogers, Jin, Leinwand, 2011, p. 1). The first wave (w1) of the HSLS:09 was conducted during the 2009-2010 academic year and included 944 schools with a subsample of on average 25 9th grade students from each school, for a total of 21,444 students. The second wave (w2) surveyed the same students again in 11th grade, and the final wave currently available (w3) surveyed the students during their expected graduation year, 2013, and includes final transcript data. Further waves are scheduled for 2016 and 2021 (Ingels, et al., 2011).

Measures.

The HSLS:09 w1 student questionnaire asked questions pertaining to student identity, utility, self-efficacy, and interest for their current science and math courses (see Table 5 for list of variables). These questions comprise 30 observed (manifest) variables that will be used in the modeling process which are theorized to be indicators of four subconstructs for each of the two content areas (math and science). Specifically, they measure students' sense of identity, utility, self-efficacy, and interest for their current math and science course, ranging from 2 to 6 items per scale. Two of the variables were dichotomized: 9th grader's favorite school subject (S1FAVSUBJ), and 9th grader's least favorite school subject (S1LEASTSUBJ). The variable

S1FAVSUBJ was used to create two new variables: MFAVSUBJ (9th grader's favorite subject is math: yes, no) and SFAVSUBJ (9th grader's favorite subject is science: yes, no). Similarly the variable S1LEASTSUBJ was also used to create two new variables: MLESTSUBJ (9th grader's least favorite subject is math: yes, no) and SLESTSUBJ (9th grader's least favorite subject is science: yes, no). Due to the nature of analyzing secondary data, the 30 observed variables do not measure the theories discussed in Chapter 3 exactly. For example, the observed variables that comprise the interest scale primarily pertain to affect or liking. These variables more closely relate to only the first phase of interest development in Hidi and Renninger's (2006) four-phase model of interest development, and do not measure the later phases.

Dependent variables include three longitudinal STEM outcome measures: students' perceived STEM career aspiration at age 30, reported in 11th grade (w2), which is a binary variable; final GPA for all STEM classes taken, reported at the end of high school (w3), which is a metrical variable; and finally, the total number of STEM credits earned by the end of high school (w3), which is a metrical variable. In summary, I will test three SEMs (one for each outcome variable) with eight first-order latent variables, and possible second-order latent variables (see Figures 8-11).

Table 5.
Variable Labels and Descriptions

Construct	*Variable Name*	*Original Name*	*Variable Label*	*Response type*
Math Identity				
	I Math Person	S1MPERSON1	You see yourself as a math person	4 Pt. Scale
	Others Math Person	S1MPERSON2	Others see you as a math person	4 Pt. Scale
Math Utility				
	Math Useful for Life	S1MUSELIFE	What students learn in this [fall 2009 math] course is useful for everyday life.	4 Pt. Scale
	Math Useful for College	S1MUSECLG	What students learn in this [fall 2009 math] course will be useful for college	4 Pt. Scale
	Math Useful for Career	S1MUSEJOB	What students learn in this [fall 2009 math] course will be useful for a future career	4 Pt. Scale
Math Self-Efficacy				
	Confident Math Tests	S1MTESTS	You are confident that you can do an excellent job on tests in this [fall 2009 math] course	4 Pt. Scale
	Understand Math Textbook	S1MTEXTBOOK	You are certain that you can understand the most difficult material presented in the textbook used in this [	4 Pt. Scale
	Skills Math Course	S1MSKILLS	You are certain that you can master the skills being taught in this [fall 2009 math] course	4 Pt. Scale
	Confident Math Assignments	S1MASSEXCL	You are confident that you can do an excellent job on assignments in this [fall 2009 math] course	4 Pt. Scale
Math Interest				
	Enjoying Math Course	S1MENJOYING	You are enjoying this [fall 2009 math] class very much	4 Pt. Scale
	Math Waste of Time	S1MWASTE	You think this [fall 2009 math] class is a waste of your time	4 Pt. Scale
	Math Boring	S1MBORING	You think this [fall 2009 math] class is boring	4 Pt. Scale
	Favorite Subject	S1FAVSUBJ	Not including lunch or study periods, what is your favorite school subject?	Nominal
	Least Favorite Subject	S1LEASTSUBJ	Not including lunch or study periods, what is your least favorite school subject?	Nominal
	Math Favorite Subject		Student's favorite subject is math	Binary
	Math Least Favorite Subject		Student’s least favorite subject is math	Binary
	Enjoys Math	S1MENJOYS	Why are you taking [fall 2009 math course]: You really enjoy math	Binary
Science Identity				
	I Science Person	S1SPERSON1	You see yourself as a science person	4 Pt. Scale
	Others Science Person	S1SPERSON2	Others see you as a science person	4 Pt. Scale
Science Utility				
	Science Useful for Life	S1SUSELIFE	What students learn in this [fall 2009 science] course is useful for everyday life.	4 Pt. Scale
	Science Useful for College	S1SUSECLG	What students learn in this [fall 2009 science] course will be useful for college	4 Pt. Scale
	Science Useful for Career	S1SUSEJOB	What students learn in this [fall 2009 science] course will be useful for a future career	4 Pt. Scale
Science Self-Efficacy				
	Confident Science Tests	S1STESTS	You are confident that you can do an excellent job on tests in this [fall 2009 science] course	4 Pt. Scale
	Understand Science Textbook	S1STEXTBOOK	You are certain that you can understand the most difficult material presented in the textbook used in this [	4 Pt. Scale
	Skills Science Course	S1SSKILLS	You are certain that you can master the skills being taught in this [fall 2009 science] course	4 Pt. Scale
	Confident Science Assignments	S1SASSEXCL	You are confident that you can do an excellent job on assignments in this [fall 2009 science] course	4 Pt. Scale
Science Interest				
	Enjoying Science Course	S1SENJOYING	You are enjoying this [fall 2009 science] class very much	4 Pt. Scale
	Science Waste of Time	S1SWASTE	You think this [fall 2009 science] class is a waste of your time	4 Pt. Scale
	Science Boring	S1SBORING	You think this [fall 2009 science] class is boring	4 Pt. Scale
	Favorite Subject	S1FAVSUBJ	Not including lunch or study periods, what is your favorite school subject?	Nominal
	Least Favorite Subject	S1LEASTSUBJ	Not including lunch or study periods, what is your least favorite school subject?	Nominal
	Science Favorite Subject		Student's favorite subject is math	Binary
	Science Least Favorite Subject		Student’s least favorite subject is math	Binary
	Enjoys Science	S1SENJOYS	Why are you taking [fall 2009 science course]: You really enjoy science	Binary

Note. Wording in brackets was replaced with the students' indicated math or science course. Variables: Math Favorite Subject, Math Least Favorite Subject, Science Favorite Subject, and Science Least Favorite Subject, were created by dichotomizing original variables Favorite Subject (S1FAVSUBJ) and Least Favorite Subject (S1LEASTSUBJ). The created dichotomized variables were not in the original survey. The 4 point scale consisted of Strongly agree, Agree, Disagree, Strongly disagree.

Data Analysis

Software.

Analyses were completed using *Mplus 7.4* (Muthen & Muthen, 1998-2015) and *SPSS 19* (IBM Corp., 2010).

Complex Survey Weights.

Both an analytic weight and its associated balanced repeated replication (BRR) weights were used in the weighted model analyses. The student analytic weight used was W3W1W2STUTR, which accounted for student non-response in the base-year, first-follow-up, and the 2013 update. BRR weights W3W1W2STUTR001- W3W1W2STUTR200 were used to account for the clustered random sampling design. Both the analytic and BRR weights need to be included to accurately compute standard errors (Ingels et al., 2015).

Missing data.

Missing data due to non-response is adjusted for using the student analytic weight. Non-response adjustments to the student base weight ensure nationally representative estimates. In the present study, any other missing data were treated as missing at random.

Model specification and selection.

Models were specified as follows: first, a single-factor model was specified in which all twelve items load onto a single common factor for both math and science. If this model fit the data well, then the items are not discriminating between separate motivational subconstructs (Model 1a-b); second, if the single-factor model was not sufficient, the measurement model for the first-order latent variables for math items, and then science items were evaluated separately (Models 2a-b); next the structural model for the first and second-order motivation latent variables for math and then science were evaluated separately (Models 3a-b); then, the math and

science factors were combined into a single model and first order and second order CFAs were conducted again (Models 4a-d); next, the unique contributions of math and science motivation were tested on each of the three STEM outcomes using the estimation methods: maximum likelihood (ML), weighted least squares minimum variance (WLSMV), and Bayesian estimation, for both unweighted and weighted models; lastly, an invariance test was conducted to determine if males and females differed in their relationships between math and/or science motivation and STEM outcomes. The Appendix displays all *Mplus* input code for the unweighted models; weighted models are available upon request from the author.

Chapter 7: Results

Descriptive Statistics

Means, standard deviations, and zero-order correlations for observed variables by sex are reported in Table 6 (Math) and Table 7 (Science).

Exploratory Factor Analysis

An exploratory factor analysis (EFA) was conducted in *Mplus* using ML estimation to determine the factor structure of the math and science motivation items without a priori constraints. After dropping the binary items: MFAVSUBJ, MLESTSUB, MENJOYS, SFAVSUBJ, SLESTSUB, and SENJOYS, results showed that a 4-factor model fit the data best for the math academic domain $\chi^2(24) = 843.701, p < .001$ compared to a 3-factor ($\Delta\chi^2(9) = 8704{,}616, p < .001$) or 5-factor ($\Delta\chi^2(8) = 481.455, p < .001$) model. A 4-factor model also fit the data best for the science academic domain $\chi^2(24) = 592.886, p < .001$ compared to a 3-($\Delta\chi^2(9) = 6149.777, p < .001$) or 5-factor ($\Delta\chi^2(8) = 429.781, p < .001$) model. For both academic domains, models with less than four factors contained higher item residuals, whereas models with more than four factors contained negative residuals (implausible values) and factors for which none of the items loaded most strongly on that factor. These results matched the factor structure intended in the HSLS:09 survey design.

Table 6.

Weighted simple (Disagreggated) Descriptive Statistics and Correlations for Math Motivation Subconstruct Observed Variables

	Males		*Females*																
Variable	*M*	*(SD)*	*M*	*(SD)*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
Math Identity																			
1. S1MPERSON1	2.59	(0.95)	2.45	(0.95)	--	.729	.191	.218	.255	.507	.484	.464	.478	.479	.287	.325	.379	.488	.459
2. S1MPERSON2	2.55	(0.91)	2.51	(0.91)	.705	--	.169	.226	.234	.479	.452	.456	.454	.420	.293	.285	.273	.381	.375
Math Utility																			
3. S1MUSELIFE	2.91	(0.83)	2.88	(0.81)	.222	.157	--	.474	.590	.263	.250	.253	.256	.340	.321	.287	.120	.110	.150
4. S1MUSECLG	3.44	(0.64)	3.42	(0.61)	.236	.219	.481	--	.607	.240	.209	.275	.266	.294	.359	.261	.096	.106	.162
5. S1MUSEJOB	3.19	(0.80)	3.15	(0.77)	.292	.258	.560	.580	--	.250	.228	.267	.266	.315	.331	.275	.121	.114	.190
Math Self-Efficacy																			
6. S1MTESTS	3.05	(0.74)	2.89	(0.76)	.494	.442	.253	.294	.269	--	.663	.684	.749	.497	.304	.331	.249	.374	.290
7. S1MTEXTBOOK	2.81	(0.81)	2.64	(0.81)	.482	.424	.234	.220	.249	.687	--	.656	.626	.429	.244	.276	.222	.313	.281
8. S1MSKILLS	3.03	(0.73)	2.94	(0.71)	.463	.424	.251	.304	.290	.686	.673	--	.722	.458	.316	.296	.212	.331	.278
9. S1MASSEXCL	3.11	(0.72)	3.03	(0.70)	.457	.416	.264	.301	.296	.748	.657	.728	--	.493	.320	.333	.213	.355	.282
Math Interest																			
10. S1MENJOYING	2.77	(0.83)	2.77	(0.82)	.472	.415	.357	.332	.356	.487	.443	.456	.485	--	.508	.590	.313	.406	.312
11. RMWASTE	3.11	(0.83)	3.21	(0.76)	.235	.221	.310	.372	.321	.272	.212	.284	.309	.497	--	.548	.191	.252	.188
12. RMBORING	2.61	(0.91)	2.70	(0.88)	.318	.293	.282	.226	.270	.297	.267	.310	.321	.567	.563	--	.250	.300	.230
13. MFAVSUBJ	0.15	(0.35)	.15	(0.35)	.331	.247	.141	.156	.175	.240	.225	.218	.233	.319	.196	.253	--	.245	.303
14. MLESTSUBJ	0.78	(0.42)	.74	(0.44)	.417	.320	.111	.088	.162	.326	.314	.291	.286	.387	.207	.311	.223	--	.246
15. S1MENJOYS	0.17	(0.38)	.18	(0.38)	.393	.339	.172	.142	.185	.254	.273	.246	.232	.334	.187	.257	.240	.209	--

Note. N=7,551 Males, N=7,637 Females (N based on students with positive weights). Pearson's bivariate (zero-order) correlations shown. Male's correlations are presented in the lower diagonal; female's correlations presented in upper diagonal. All correlations are significant at the <.001 level.

Table 7.

Weighted simple (Disagreggated) Descriptive Statistics and Correlations for Science Motivation Subconstruct Observed Variables

	Males		*Females*																
Variable	*M*	*(SD)*	*M*	*(SD)*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
Science Identity																			
1. S1SPERSON1	2.39	(0.91)	2.27	(0.86)	--	.720	.317	.298	.378	.382	.407	.409	.393	.422	.321	.309	.301	.286	.415
2. S1SPERSON2	2.27	(0.86)	2.26	(0.82)	.709	--	.266	.268	.316	.367	.389	.395	.385	.365	.298	.253	.243	.222	.345
Science Utility																			
3. S1SUSELIFE	2.63	(0.79)	2.67	(0.75)	.320	.269	--	.471	.475	.314	.264	.283	.297	.400	.359	.324	.116	.174	.233
4. S1SUSECLG	3.22	(0.67)	3.20	(0.65)	.324	.262	.458	--	.586	.283	.214	.311	.315	.335	.343	.250	.095	.143	.216
5. S1SUSEJOB	2.86	(0.85)	2.91	(0.83)	.384	.324	.522	.545	--	.263	.251	.295	.293	.329	.319	.245	.136	.146	.255
Science Self-Efficacy																			
6. S1STESTS	2.95	(0.73)	2.77	(0.73)	.404	.371	.298	.298	.302	--	.608	.646	.674	.450	.327	.319	.178	.273	.225
7. S1STEXTBOOK	2.73	(0.77)	2.55	(0.76)	.413	.393	.305	.265	.294	.640	--	.628	.577	.382	.258	.263	.157	.234	.227
8. S1SSKILLS	2.92	(0.73)	2.82	(0.70)	.427	.395	.312	.296	.316	.640	.642	--	.674	.424	.357	.329	.169	.260	.264
9. S1SASSEXCL	3.02	(0.70)	2.96	(0.68)	.406	.343	.312	.315	.323	.706	.606	.683	--	.435	.334	.304	.158	.263	.234
Science Interest																			
10. S1SENJOYING	2.80	(0.84)	2.74	(0.82)	.418	.365	.452	.400	.400	.452	.415	.439	.450	--	.558	.610	.254	.397	.287
11. RSWASTE	3.07	(0.81)	3.12	(0.76)	.293	.276	.407	.389	.398	.316	.288	.318	.352	.575	--	.614	.181	.308	.249
12. RSBORING	2.71	(0.91)	2.69	(0.88)	.289	.271	.368	.315	.342	.307	.293	.309	.307	.587	.625	--	.222	.320	.246
13. SFAVSUBJ	.10	(0.30)	.09	(0.28)	.283	.218	.145	.158	.184	.178	.171	.185	.179	.261	.168	.221	--	.149	.236
14. SLESTSUBJ	.85	(0.35)	.81	(0.39)	.289	.220	.150	.148	.163	.255	.246	.213	.239	.374	.231	.266	.136	--	.169
15. S1SENJOYS	.18	(0.38)	.16	(0.36)	.388	.343	.213	.198	.238	.237	.249	.256	.243	.303	.254	.252	.229	.167	--

Note. N=7,551 Males, N=7,637 Females (N based on students with positive weights). Pearson's bivariate (zero-order) correlations shown. Male's correlations are presented in the lower diagonal; female's correlations presented in upper diagonal. All correlations are significant at the <.001 level.

Results for Models 1a-b and 2a-b

As discussed previously, the single factor model tests the most parsimonious model where all items load onto a single common factor (or general factor). If the single factor model fit the data well, then we can assume that the items are all related to a general motivational construct that is not distinguishing between the four hypothesized motivational subconstructs (Geiser, 2013).

Model fit statistics are provided in Table 8. Results showed that for both the math and science measurement models, the 4-factor Models (2a, b) were a better fit to the data. The chi-square, BIC, RMSEA, and SRMR values were lower for Models 2a, b than for Models 1a, b; and the CFI values were higher for Models 2a, b than Models 1a, b, all indicating that the 4-factor model was a better fit for both the math and science items. These results are in line with the EFA findings which also identified a 4-factor model as the best fit.

Table 8.
Model fit statistics

	Number Parameters Estimated	*Model fit* χ^2	(df)	*p*	BIC	RMSEA	CFI	SRMR
Model 1a (1-factor) math	24	34147.73	(66)	<.001	577991.05	0.155	0.71	0.11
Model 1b (1-factor) science	24	30371.94	(66)	<.001	544823.61	0.147	0.70	0.10
Model 2a (4-factor) math	30	3694.32	(60)	<.001	547597.47	0.053	0.97	0.04
Model 2b (4-factor) science	30	2812.57	(60)	<.001	517324.07	0.046	0.97	0.03
Model 3a math	28	4384.28	(62)	<.001	548267.49	0.057	0.96	0.05
Model 3b science	28	3190.91	(62)	<.001	517682.47	0.049	0.97	0.04
Model 4a	76	15448.55	(248)	<.001	1057371.34	0.053	0.94	0.04
Model 4b	64	18233.95	(260)	<.001	1060037.06	0.057	0.92	0.10
Model 4c	57	21421.52	(267)	<.001	1063154.83	0.061	0.91	0.06
Model 4d	62	28774.13	(262)	<.001	1070557.30	0.071	0.88	0.09
STEM Credits	86	15635.50	(264)	<.001	1161575.04	0.050	0.94	0.03
STEM GPA	86	16028.93	(264)	<.001	1113038.03	0.051	0.93	0.04
STEM Career	145	31437.85	(399)	<.001		0.058	0.95	

Table 9 provides standardized path coefficients and test statistics for math and science variables. Results showed that each of the path coefficients for math and science were significant

(z more extreme than ±1.96). Standardized path loadings for math ranged from 0.66 to 0.90 and factor intercorrelations ranged from 0.38 (Math Identity-Math Utility) to 0.66 (Math Identity-Math Self-efficacy). Standardized path loadings for science ranged from 0.65 to 0.89 and factor intercorrelations ranged from 0.49 (Science Utility-Science Self-efficacy) to 0.62 (Science Utility-Science Interest). The moderate factor intercorrelations and theoretical framework discussed earlier, provide evidence for a potential second order factor. A second order factor model allows for a common factor across the sub-factors, thus allowing for domain-specific variability (Geiser, 2013), as opposed to simply a single factor model (which was already shown to be a poor fit to the data).

Table 9.
Standardized Path Coefficients and Test Statistics (Z) for math and science academic domains

	Model 2a Math		Model 2b Science	
Relationship	Path	Z	Path	Z
Factor-Measure				
Math Identity-MID1	0.90	245.85	0.89	211.83
Math Identity-MID2	0.81	207.95	0.81	187.37
Math Utility-MUT1	0.69	138.85	0.65	114.84
Math Utility-MUT2	0.71	149.22	0.71	137.13
Math Utility-MUT3	0.82	192.62	0.77	159.12
Math Self-efficacy-MSE1	0.84	321.07	0.82	259.41
Math Self-efficacy-MSE2	0.79	243.72	0.77	209.92
Math Self-efficacy-MSE3	0.83	304.54	0.83	266.50
Math Self-efficacy-MSE4	0.85	331.96	0.82	255.80
Math Interest-MIN1	0.81	180.48	0.79	183.30
Math Interest-MIN2	0.66	119.91	0.74	158.51
Math Interest-MIN3	0.72	144.03	0.75	167.02
Factor intercorrelations				
Math Identity-Math Utility	0.38	48.43	0.51	68.53
Math Identity-Math Self-efficacy	0.66	124.58	0.58	93.26
Math Identity-Math Interest	0.57	85.12	0.52	72.15
Math Utility-Math Self-efficacy	0.43	58.32	0.49	65.76
Math Utility-Math Interest	0.56	77.25	0.62	88.33
Math Self-efficacy-Math Interest	0.60	94.41	0.58	87.95

Results for Model 3a-b

Model 3a, b tested a second order math (3a) and science (3b) motivation latent variable; fit statistics are shown in Table 7. Model 3a, b was a significantly worse fit than model 2a, b. This suggests that there is not an underlying second order factor structure. Therefore, the better fitting first order 4-factor model (2a, b) was retained. Next, math and science items were combined into one model.

Results for Model 4a-d

Model 4 included both math and science items in a single model. Fit statistics for Model 4a, b, c, d are shown in Table 8. Model 4a tested a first order model where all factors were correlated (see Figure 7). Model 4b tested a first order model where only matching math and science factors were correlated (for example math utility was correlated with science utility) and all math factors correlated and all science factors correlated (Figure 8). Model 4c tested a second order factor model with 2 second order factors, math motivation and science motivation (Figure 9). Finally, Model 4d tested a second order factor model with 4 second order factors where matching math and science items shared a second order factor (for example math and science utility factors made up the second order utility factor) (Figure 10). Results showed that model 4a was the best fitting model and that a second order factor structure was not supported (See Table 8).

Table 10 provides standardized path coefficients and test statistics for model 4a. Results showed that each of the path coefficients were significant. Factor intercorrelations ranged from 0.15 (Math Utility-Science Identity) to 0.66 (Math Identity-Math Self-efficacy). For the most part math factors were correlated highest with other math factors and science factors with other science factors, however some between subject correlations were notable: Math Utility and

Science Utility were correlated at 0.55, and Math Self-Efficacy and Science Self-Efficacy were correlated at 0.45.

Table 10.
ML Estimated Standardized Path Coefficients and Test Statistics (Z) for Math and Science Combined Model

	Model 4a	
Relationship	Path	Z
Factor-Measure		
Math Identity-MID1	0.88	242.88
Math Identity-MID2	0.83	220.31
Math Utility-MUT1	0.69	141.02
Math Utility-MUT2	0.72	154.26
Math Utility-MUT3	0.82	203.17
Math Self-efficacy-MSE1	0.84	320.67
Math Self-efficacy-MSE2	0.79	246.02
Math Self-efficacy-MSE3	0.84	309.77
Math Self-efficacy-MSE4	0.85	334.40
Math Interest-MIN1	0.80	180.56
Math Interest-MIN2	0.67	124.95
Math Interest-MIN3	0.72	148.67
Science Identity-SID1	0.88	217.78
Science Identity-SID2	0.83	201.30
Science Utility-SUT1	0.65	118.52
Science Utility-SUT2	0.72	144.37
Science Utility-SUT3	0.77	167.79
Science Self-efficacy-SSE1	0.82	260.86
Science Self-efficacy-SSE2	0.77	213.02
Science Self-efficacy-SSE3	0.83	271.63
Science Self-efficacy-SSE4	0.82	258.74
Science Interest-SIN1	0.79	184.12
Science Interest-SIN2	0.75	162.80
Science Interest-SIN3	0.75	169.62
Factor intercorrelations		
Math Identity-Math Utility	0.38	48.34
Math Identity-Math Self-efficacy	0.66	127.64
Math Identity-Math Interest	0.57	84.10
Math Utility-Math Self-efficacy	0.43	58.59
Math Utility-Math Interest	0.56	77.68
Math Self-efficacy-Math Interest	0.59	93.09
Science Identity-Science Utility	0.51	68.98
Science Identity-Science Self-efficacy	0.59	96.23
Science Identity-Science Interest	0.52	72.00
Science Utility-Science Self-efficacy	0.49	66.09
Science Utility-Science Interest	0.62	88.92
Science Self-efficacy-Science interest	0.58	87.75
Math Identity-Science Identity	0.31	39.92
Math Identity-Science Utility	0.24	27.34
Math Identity- Science Self-efficacy	0.29	36.96
Math Identity-Science Interest	0.18	20.97
Math Utility-Science Identity	0.15	17.13
Math Utility-Science Utility	0.55	72.23
Math Utility-Science Self-efficacy	0.23	26.06
Math Utility-Science Interest	0.27	29.91
Math Self-efficacy-Science Identity	0.22	28.03
Math Self-efficacy-Science Utility	0.25	29.35
Math Self-efficacy-Science Self-efficacy	0.45	64.05
Math Self-efficacy-Science Interest	0.20	23.14
Math Interest-Science Identity	0.18	20.32
Math Interest-Science Utiltiy	0.33	36.40
Math Interest-Secience Self-efficacy	0.23	26.52
Math Interest-Science Interest	0.34	38.30

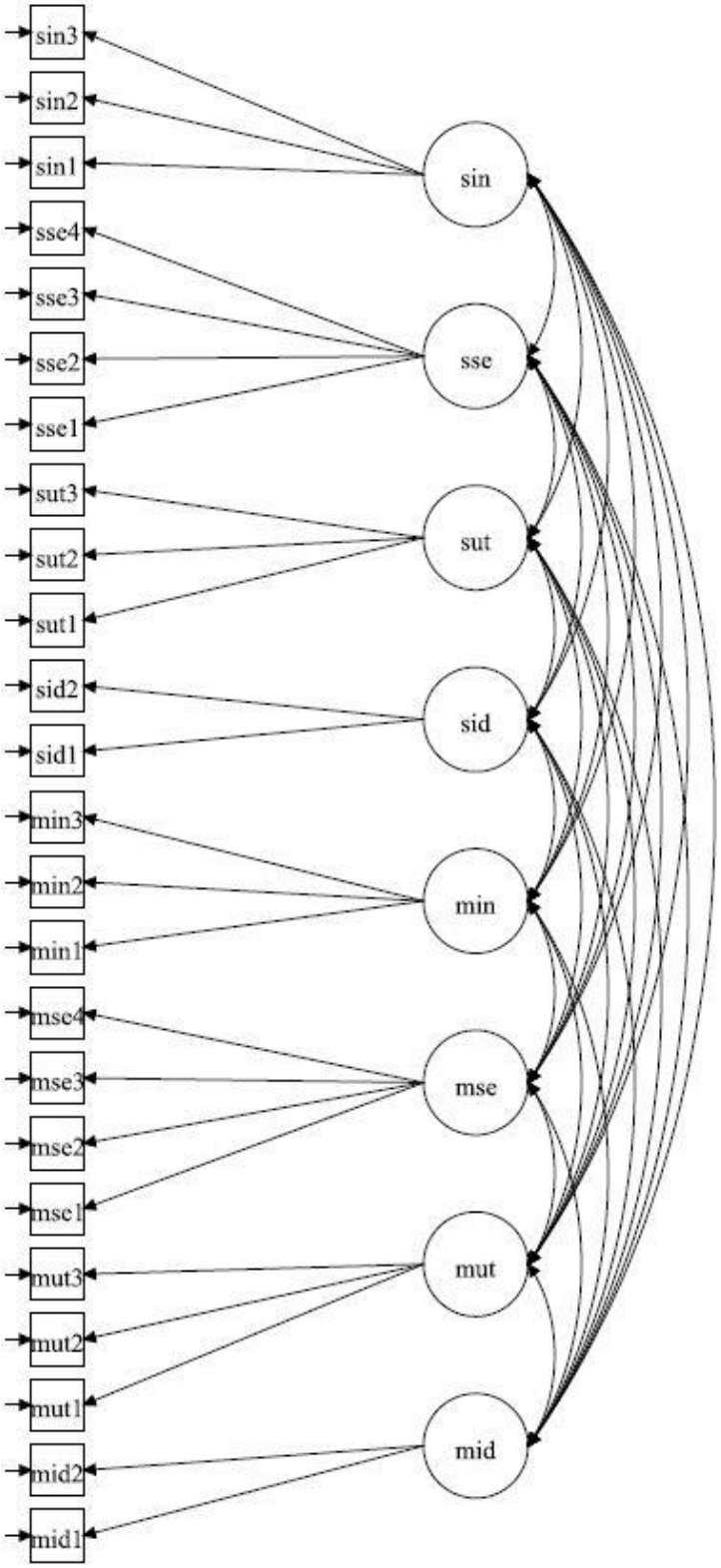


Figure 7. Model 4a

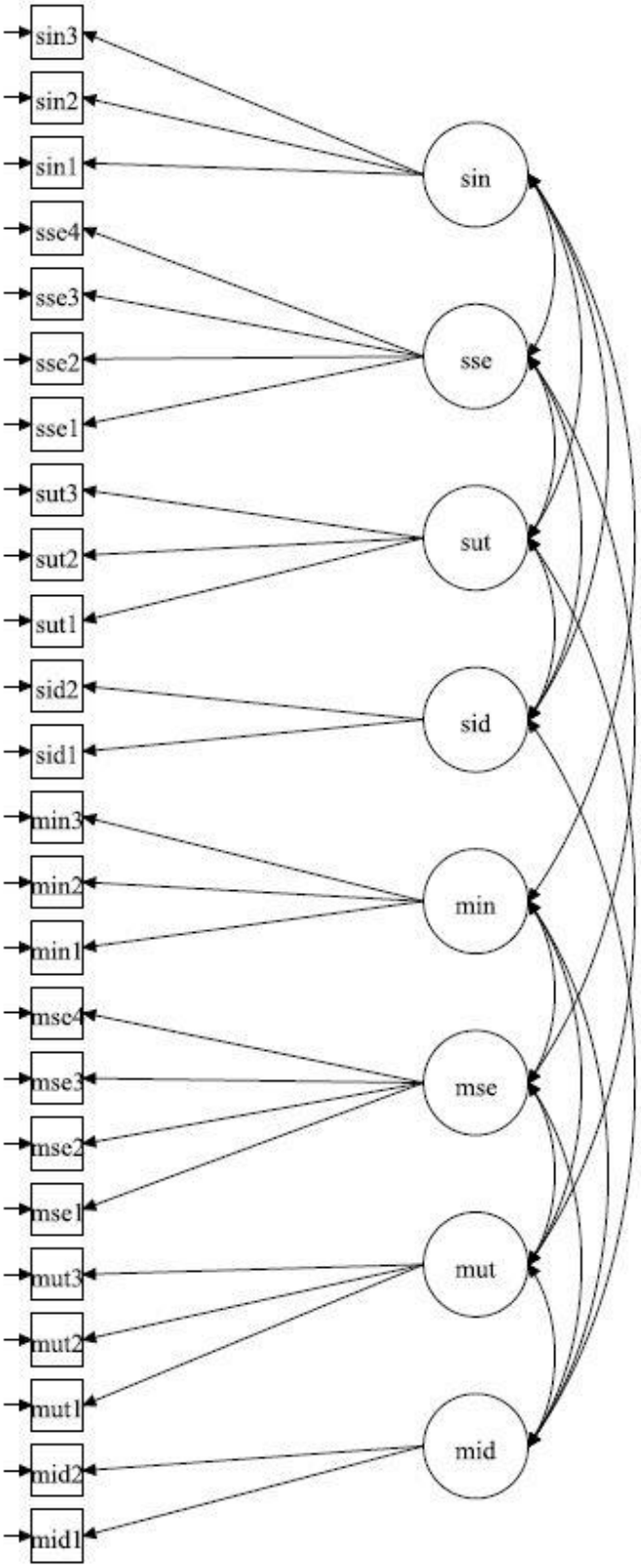


Figure 8. Model 4b

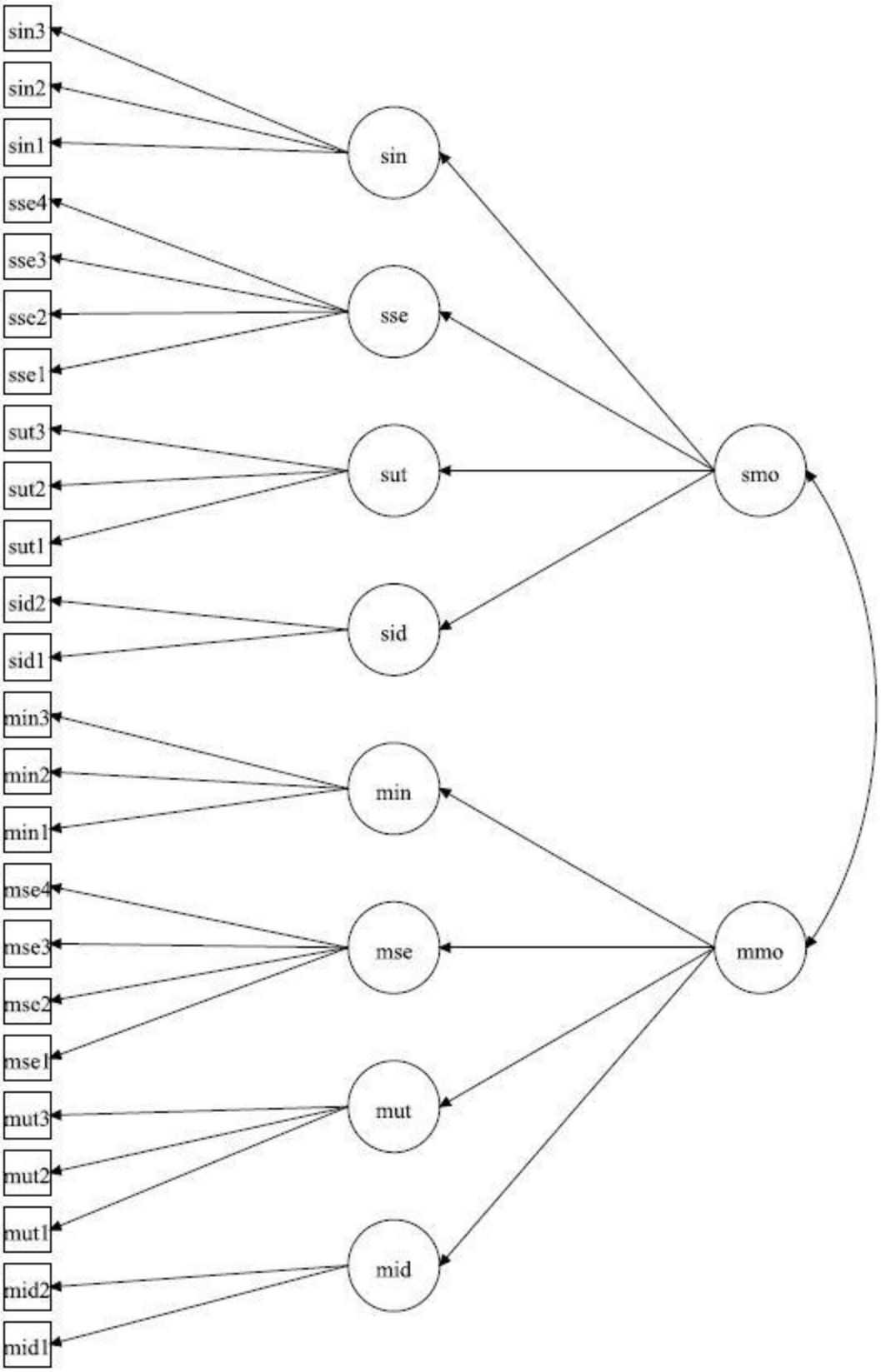


Figure 9. Model 4c

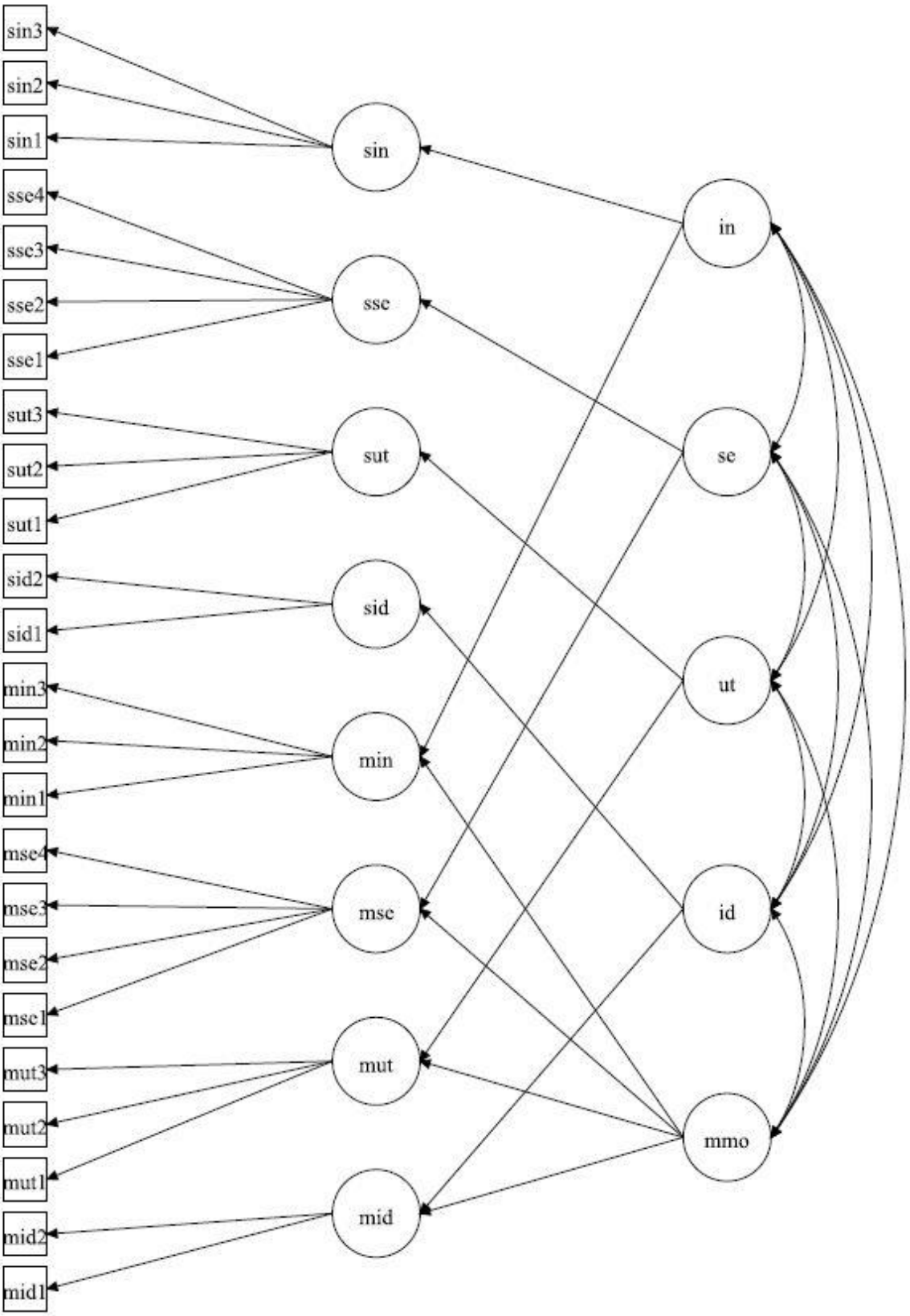


Figure 10. Model 4d

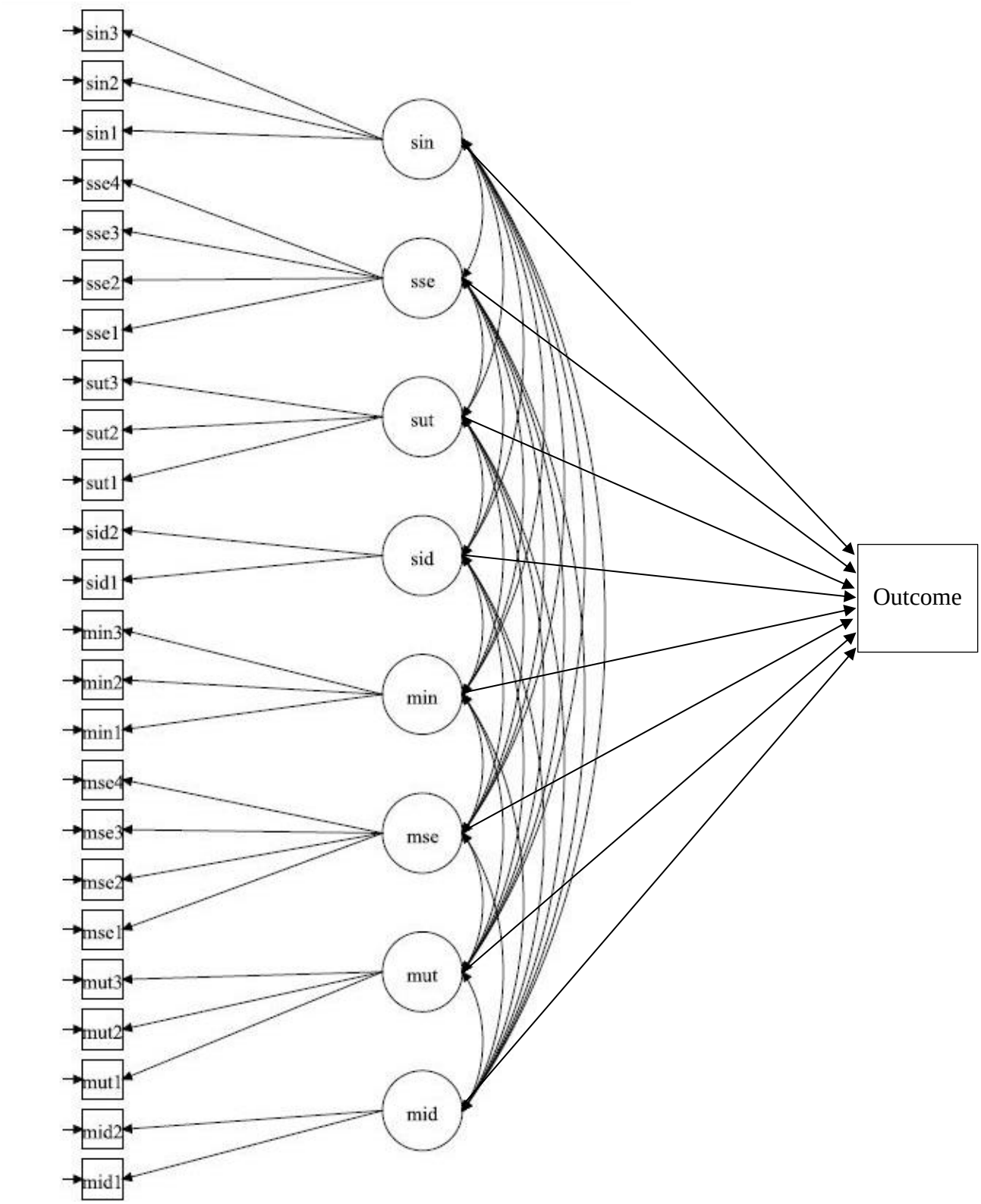


Figure 11. General Outcome Model

Results for Outcome Models

Figure 11 shows the general outcome model with each factor predicting the outcome and all factors correlated.

STEM credits.

The first set of columns in Table 11 provides the standardized and unstandardized results of the STEM Credits outcome model using ML estimation without weights. Recall that the outcome variable STEM Credits is the total number of STEM credits earned by the end of high school. Results for the measurement portion of the model (path loadings from the indicators to factors and factor correlations) were the same as stated previously in the CFA results for model 4a. Looking at the bottom of Table 11, we see that all factors, except for Science Utility, uniquely significantly predicted the number of STEM credits earned at the end of high school. Math Identity was the strongest predictor of STEM Credits with an unstandardized loading of 0.34, while Math and Science Interest were the weakest predictors with an unstandardized loading of 0.09. Also, Math Utility was significantly negatively predictive of the number of STEM credits earned, indicating a potential suppressor effect.

Table 11.

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM Credits by Various Estimation Methods

	STEM CREDITS													
	ML Est No Weights				ML Est Weights		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
Factor-Measure														
Math Identity-MID1	0.88	244.84	0.88	140.20	0.87	75.40	0.88	(0.004)	0.87	0.88	0.88	(0.006)	0.87	0.891
Math Identity-MID2	0.83	223.26	0.83	131.07	0.82	62.42	0.83	(0.004)	0.82	0.84	0.83	(0.006)	0.82	0.842
Math Utility-MUT1	0.69	141.27	0.69	97.98	0.69	49.10	0.69	(0.004)	0.68	0.70	0.69	(0.007)	0.68	0.701
Math Utility-MUT2	0.72	153.99	0.72	103.03	0.72	40.12	0.72	(0.005)	0.71	0.73	0.72	(0.007)	0.71	0.732
Math Utility-MUT3	0.82	203.31	0.82	121.43	0.82	48.93	0.82	(0.004)	0.81	0.83	0.82	(0.006)	0.81	0.834
Math Self-efficacy-MSE1	0.84	320.99	0.84	140.30	0.85	63.90	0.84	(0.003)	0.84	0.85	0.84	(0.006)	0.83	0.854
Math Self-efficacy-MSE2	0.79	245.90	0.79	126.54	0.78	69.57	0.79	(0.003)	0.78	0.80	0.79	(0.006)	0.78	0.801
Math Self-efficacy-MSE3	0.84	310.06	0.84	138.43	0.83	54.68	0.84	(0.002)	0.83	0.84	0.84	(0.006)	0.83	0.847
Math Self-efficacy-MSE4	0.85	335.14	0.85	142.25	0.86	55.16	0.85	(0.003)	0.85	0.86	0.85	(0.006)	0.84	0.861
Math Interest-MIN1	0.80	180.23	0.80	114.67	0.81	52.22	0.80	(0.004)	0.79	0.81	0.80	(0.007)	0.79	0.811
Math Interest-MIN2	0.67	125.23	0.67	91.74	0.67	30.77	0.67	(0.005)	0.66	0.68	0.67	(0.007)	0.66	0.684
Math Interest-MIN3	0.72	148.92	0.72	101.84	0.72	45.15	0.72	(0.004)	0.71	0.73	0.72	(0.006)	0.71	0.731
Science Identity-SID1	0.88	219.63	0.88	134.60	0.88	56.75	0.87	(0.004)	0.87	0.88	0.88	(0.006)	0.86	0.885
Science Identity-SID2	0.83	203.19	0.83	126.29	0.82	56.98	0.83	(0.004)	0.82	0.84	0.83	(0.006)	0.82	0.843
Science Utility-SUT1	0.65	118.50	0.65	86.87	0.67	40.75	0.65	(0.006)	0.64	0.66	0.65	(0.007)	0.63	0.664
Science Utility-SUT2	0.72	144.28	0.72	97.84	0.72	32.34	0.71	(0.005)	0.71	0.72	0.71	(0.007)	0.70	0.728
Science Utility-SUT3	0.77	167.80	0.77	107.23	0.75	47.44	0.77	(0.005)	0.76	0.78	0.77	(0.007)	0.76	0.786
Science Self-efficacy-SSE1	0.82	260.96	0.82	127.63	0.81	51.63	0.82	(0.003)	0.81	0.83	0.82	(0.007)	0.81	0.829
Science Self-efficacy-SSE2	0.77	212.87	0.77	116.95	0.76	50.99	0.77	(0.003)	0.77	0.78	0.77	(0.007)	0.76	0.784
Science Self-efficacy-SSE3	0.83	271.64	0.83	129.60	0.82	53.32	0.83	(0.003)	0.82	0.83	0.83	(0.007)	0.81	0.839
Science Self-efficacy-SSE4	0.82	259.14	0.82	126.95	0.82	50.12	0.82	(0.003)	0.81	0.82	0.82	(0.006)	0.80	0.829
Science Interest-SIN1	0.79	183.91	0.79	112.31	0.79	50.71	0.79	(0.004)	0.78	0.80	0.79	(0.007)	0.77	0.799
Science Interest-SIN2	0.75	163.04	0.75	104.83	0.76	38.85	0.75	(0.005)	0.74	0.76	0.75	(0.007)	0.73	0.761
Science Interest-SIN3	0.75	169.75	0.75	106.85	0.76	49.99	0.75	(0.005)	0.74	0.76	0.75	(0.007)	0.74	0.766

Table 11. Continued

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM Credits by Various Estimation Methods

	STEM CREDITS													
	ML Est No Weights				ML Est Weights		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
Factor intercorrelations														
Math Identity-Math Utility	0.38	48.29	0.38	48.29	0.36	19.36	0.38	(0.008)	0.36	0.39	0.38	(0.008)	0.36	0.39
Math Identity-Math Self-efficacy	0.66	127.82	0.66	127.82	0.65	43.66	0.66	(0.006)	0.65	0.67	0.66	(0.006)	0.65	0.67
Math Identity-Math Interest	0.57	84.01	0.57	84.01	0.57	37.48	0.57	(0.007)	0.56	0.58	0.57	(0.007)	0.56	0.58
Math Utility-Math Self-efficacy	0.43	58.56	0.43	58.56	0.42	19.53	0.43	(0.007)	0.41	0.44	0.43	(0.007)	0.41	0.44
Math Utility-Math Interest	0.56	77.68	0.56	77.68	0.55	31.23	0.56	(0.007)	0.54	0.57	0.56	(0.007)	0.54	0.57
Math Self-efficacy-Math Interest	0.59	93.03	0.59	93.03	0.60	35.00	0.59	(0.007)	0.58	0.61	0.59	(0.007)	0.58	0.61
Science Identity-Science Utility	0.51	68.96	0.51	68.96	0.52	25.25	0.51	(0.008)	0.50	0.53	0.51	(0.008)	0.50	0.53
Science Identity-Science Self-efficacy	0.59	96.26	0.59	96.26	0.58	43.02	0.59	(0.006)	0.58	0.60	0.59	(0.006)	0.58	0.60
Science Identity-Science Interest	0.52	71.95	0.52	71.95	0.51	22.78	0.52	(0.008)	0.50	0.53	0.52	(0.008)	0.50	0.53
Science Utility-Science Self-efficacy	0.49	66.10	0.49	66.10	0.50	33.00	0.49	(0.007)	0.48	0.51	0.49	(0.007)	0.48	0.51
Science Utility-Science Interest	0.62	88.95	0.62	88.95	0.64	30.74	0.62	(0.007)	0.61	0.64	0.62	(0.007)	0.61	0.64
Science Self-efficacy-Science interest	0.58	87.75	0.58	87.75	0.58	32.87	0.58	(0.007)	0.57	0.59	0.58	(0.007)	0.57	0.59
Math Identity-Science Identity	0.31	40.18	0.31	40.18	0.31	16.21	0.32	(0.008)	0.30	0.33	0.32	(0.008)	0.30	0.33
Math Identity-Science Utility	0.24	27.41	0.24	27.41	0.24	12.78	0.24	(0.009)	0.23	0.26	0.24	(0.009)	0.23	0.26
Math Identity- Science Self-efficacy	0.30	37.15	0.30	37.15	0.29	16.00	0.30	(0.008)	0.28	0.31	0.30	(0.008)	0.28	0.31
Math Identity-Science Interest	0.18	21.05	0.18	21.05	0.20	10.80	0.18	(0.009)	0.17	0.20	0.18	(0.009)	0.17	0.20
Math Utility-Science Identity	0.15	17.11	0.15	17.11	0.17	9.09	0.15	(0.008)	0.13	0.17	0.15	(0.008)	0.13	0.17
Math Utility-Science Utility	0.55	72.23	0.55	72.23	0.55	22.53	0.56	(0.008)	0.54	0.57	0.56	(0.008)	0.54	0.57
Math Utility-Science Self-efficacy	0.23	26.05	0.23	26.05	0.24	12.57	0.23	(0.009)	0.21	0.24	0.23	(0.009)	0.21	0.24
Math Utility-Science Interest	0.27	29.93	0.27	29.93	0.26	11.96	0.27	(0.009)	0.25	0.28	0.27	(0.009)	0.25	0.28
Math Self-efficacy-Science Identity	0.22	28.06	0.22	28.06	0.22	11.94	0.22	(0.008)	0.20	0.24	0.22	(0.008)	0.20	0.24
Math Self-efficacy-Science Utility	0.25	29.37	0.25	29.37	0.26	12.07	0.25	(0.009)	0.24	0.27	0.25	(0.009)	0.24	0.27
Math Self-efficacy-Science Self-efficacy	0.45	64.15	0.45	64.15	0.45	25.54	0.45	(0.007)	0.43	0.46	0.45	(0.007)	0.43	0.46
Math Self-efficacy-Science Interest	0.20	23.18	0.20	23.18	0.20	8.04	0.20	(0.009)	0.18	0.22	0.20	(0.009)	0.18	0.22
Math Interest-Science Identity	0.18	20.33	0.18	20.33	0.18	11.74	0.18	(0.009)	0.16	0.19	0.18	(0.009)	0.16	0.19
Math Interest-Science Utiltiy	0.33	36.43	0.33	36.43	0.35	17.02	0.33	(0.009)	0.31	0.35	0.33	(0.009)	0.31	0.35
Math Interest-Secience Self-efficacy	0.23	26.59	0.23	26.59	0.25	13.65	0.23	(0.009)	0.21	0.25	0.23	(0.009)	0.21	0.25
Math Interest-Science Interest	0.34	38.38	0.34	38.38	0.38	15.44	0.34	(0.009)	0.32	0.35	0.34	(0.009)	0.32	0.35
Factor-Outcome														
Math Identity	**0.13**	9.85	**0.34**	9.82	**0.28**	3.91	**0.13**	(0.013)	0.10	0.15	**0.34**	(0.034)	0.26	0.39
Math Utility	**-0.07**	-4.72	**-0.19**	-4.72	-0.07	-0.66	**-0.07**	(0.014)	-0.10	-0.05	**-0.20**	(0.039)	-0.28	-0.12
Math Self-efficacy	**0.09**	6.18	**0.25**	6.18	**0.17**	2.24	**0.09**	(0.014)	0.06	0.12	**0.25**	(0.038)	0.17	0.33
Math Interst	**0.04**	2.31	**0.09**	2.31	0.12	1.67	**0.04**	(0.016)	0.01	0.07	**0.09**	(0.044)	0.01	0.18
Science Identity	**0.09**	7.50	**0.25**	7.48	**0.19**	3.35	**0.09**	(0.012)	0.07	0.12	**0.25**	(0.031)	0.19	0.31
Science Utility	0.00	0.02	0.00	0.02	-0.06	-0.50	0.00	(0.018)	-0.03	0.03	0.00	(0.049)	-0.09	0.09
Science Self-efficacy	**0.05**	3.05	**0.12**	3.05	**0.17**	2.47	**0.04**	(0.014)	0.02	0.07	**0.12**	(0.038)	0.05	0.19
Science Interest	**0.03**	2.10	**0.09**	2.10	0.03	0.43	**0.04**	(0.016)	0.00	0.07	**0.10**	(0.044)	0.01	0.18
R^2			0.08			0.07					0.08			

Note: Bayesian significance test based on a one-tailed p-value.

STEM GPA.

The first set of columns in Table 12 provides the results of the STEM GPA outcome model using ML estimation without weights. Recall that the outcome variable STEM GPA, is the final GPA for all STEM classes taken, reported at the end of high school. Looking at the bottom of Table 12, we see that all factors, except for Science Interest, uniquely significantly predicted STEM GPA. Math Identity was the strongest predictor of STEM GPA with an unstandardized loading of 0.24, while Science Utility was the weakest predictor with an unstandardized loading of 0.04. Again, Math Utility was a significant negative predictor of the outcome.

Table 12.

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM GPA by Various Estimation Methods

	STEM GPA													
	ML Est No Weights				ML Est Weights		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
Factor-Measure														
Math Identity-MID1	0.87	247.99	0.87	139.95	0.86	75.68	0.87	(0.004)	0.86	0.88	0.87	(0.006)	0.86	0.88
Math Identity-MID2	0.84	232.12	0.84	133.52	0.83	64.63	0.84	(0.003)	0.83	0.84	0.84	(0.006)	0.83	0.85
Math Utility-MUT1	0.69	142.49	0.69	98.48	0.70	49.03	0.69	(0.005)	0.68	0.70	0.69	(0.007)	0.68	0.71
Math Utility-MUT2	0.72	153.47	0.72	102.77	0.72	40.47	0.72	(0.005)	0.71	0.72	0.72	(0.007)	0.70	0.73
Math Utility-MUT3	0.82	204.35	0.82	121.63	0.82	50.21	0.82	(0.004)	0.81	0.83	0.82	(0.007)	0.81	0.83
Math Self-efficacy-MSE1	0.84	321.06	0.84	140.37	0.85	63.89	0.84	(0.003)	0.84	0.85	0.84	(0.005)	0.83	0.85
Math Self-efficacy-MSE2	0.79	245.04	0.79	126.41	0.78	69.48	0.79	(0.003)	0.78	0.79	0.79	(0.006)	0.78	0.80
Math Self-efficacy-MSE3	0.84	310.20	0.84	138.50	0.83	54.63	0.84	(0.002)	0.83	0.84	0.84	(0.005)	0.83	0.85
Math Self-efficacy-MSE4	0.85	336.56	0.85	142.52	0.86	55.35	0.85	(0.003)	0.85	0.86	0.85	(0.005)	0.84	0.86
Math Interest-MIN1	0.80	179.57	0.80	114.44	0.81	52.49	0.79	(0.005)	0.79	0.80	0.79	(0.007)	0.78	0.81
Math Interest-MIN2	0.67	125.67	0.67	91.96	0.67	30.82	0.67	(0.005)	0.66	0.68	0.67	(0.007)	0.66	0.68
Math Interest-MIN3	0.72	149.23	0.72	101.97	0.72	45.15	0.72	(0.004)	0.71	0.73	0.72	(0.006)	0.71	0.73
Science Identity-SID1	0.87	218.16	0.87	133.78	0.87	56.72	0.87	(0.004)	0.86	0.88	0.87	(0.006)	0.86	0.88
Science Identity-SID2	0.83	205.04	0.83	127.12	0.82	57.50	0.83	(0.004)	0.83	0.84	0.83	(0.007)	0.82	0.85
Science Utility-SUT1	0.65	118.55	0.65	86.89	0.67	40.80	0.65	(0.005)	0.64	0.66	0.65	(0.007)	0.64	0.67
Science Utility-SUT2	0.71	144.23	0.72	97.82	0.72	32.19	0.71	(0.004)	0.70	0.72	0.71	(0.007)	0.70	0.73
Science Utility-SUT3	0.77	167.70	0.77	107.20	0.75	47.53	0.77	(0.005)	0.76	0.78	0.77	(0.007)	0.75	0.78
Science Self-efficacy-SSE1	0.82	261.39	0.82	127.70	0.82	51.51	0.82	(0.003)	0.81	0.83	0.82	(0.006)	0.81	0.83
Science Self-efficacy-SSE2	0.77	212.44	0.77	116.84	0.76	50.70	0.77	(0.004)	0.76	0.78	0.77	(0.006)	0.76	0.79
Science Self-efficacy-SSE3	0.83	271.46	0.83	129.54	0.82	53.14	0.83	(0.003)	0.82	0.83	0.83	(0.006)	0.82	0.84
Science Self-efficacy-SSE4	0.82	259.84	0.82	127.08	0.82	50.28	0.82	(0.003)	0.81	0.82	0.82	(0.007)	0.81	0.83
Science Interest-SIN1	0.79	183.65	0.79	112.28	0.79	50.82	0.79	(0.004)	0.78	0.79	0.79	(0.007)	0.78	0.80
Science Interest-SIN2	0.75	162.58	0.75	104.69	0.76	38.65	0.75	(0.005)	0.74	0.76	0.75	(0.007)	0.73	0.76
Science Interest-SIN3	0.75	169.66	0.75	106.84	0.76	49.96	0.75	(0.005)	0.75	0.76	0.75	(0.007)	0.74	0.77

Table 12. Continued

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM GPA by Various Estimation Methods

	STEM GPA													
	ML Est No Weights				ML Est Weights		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
Factor intercorrelations														
Math Identity-Math Utility	0.38	48.13	0.38	48.13	0.36	19.47	0.38	(0.008)	0.36	0.39	0.38	(0.008)	0.36	0.39
Math Identity-Math Self-efficacy	0.66	127.47	0.66	127.47	0.65	43.58	0.66	(0.006)	0.65	0.67	0.66	(0.006)	0.65	0.67
Math Identity-Math Interest	0.57	83.34	0.57	83.34	0.56	37.17	0.57	(0.007)	0.56	0.58	0.57	(0.007)	0.56	0.58
Math Utility-Math Self-efficacy	0.43	58.55	0.43	58.55	0.42	19.54	0.43	(0.007)	0.41	0.44	0.43	(0.007)	0.41	0.44
Math Utility-Math Interest	0.56	77.77	0.56	77.77	0.55	31.28	0.56	(0.007)	0.54	0.57	0.56	(0.007)	0.54	0.57
Math Self-efficacy-Math Interest	0.59	92.78	0.59	92.78	0.60	34.96	0.59	(0.007)	0.58	0.61	0.59	(0.007)	0.58	0.61
Science Identity-Science Utility	0.51	68.77	0.51	68.77	0.52	25.02	0.51	(0.008)	0.50	0.53	0.51	(0.008)	0.50	0.53
Science Identity-Science Self-efficacy	0.59	96.44	0.59	96.44	0.58	43.54	0.59	(0.006)	0.58	0.60	0.59	(0.006)	0.58	0.60
Science Identity-Science Interest	0.52	71.70	0.52	71.70	0.51	22.74	0.52	(0.007)	0.50	0.53	0.52	(0.007)	0.50	0.53
Science Utility-Science Self-efficacy	0.49	66.14	0.49	66.14	0.50	32.99	0.49	(0.008)	0.48	0.51	0.49	(0.008)	0.48	0.51
Science Utility-Science Interest	0.62	88.95	0.62	88.95	0.64	30.72	0.62	(0.008)	0.61	0.64	0.62	(0.008)	0.61	0.64
Science Self-efficacy-Science interest	0.58	87.76	0.58	87.76	0.57	32.86	0.58	(0.007)	0.56	0.59	0.58	(0.007)	0.56	0.59
Math Identity-Science Identity	0.32	41.20	0.32	41.20	0.32	16.71	0.32	(0.008)	0.31	0.34	0.32	(0.008)	0.31	0.34
Math Identity-Science Utility	0.24	27.54	0.24	27.54	0.24	12.79	0.25	(0.009)	0.23	0.26	0.25	(0.009)	0.23	0.26
Math Identity- Science Self-efficacy	0.30	37.50	0.30	37.50	0.30	16.36	0.30	(0.007)	0.29	0.31	0.30	(0.007)	0.29	0.31
Math Identity-Science Interest	0.18	21.12	0.18	21.12	0.20	10.85	0.19	(0.008)	0.17	0.20	0.19	(0.008)	0.17	0.20
Math Utility-Science Identity	0.15	17.06	0.15	17.06	0.17	9.16	0.15	(0.009)	0.13	0.17	0.15	(0.009)	0.13	0.17
Math Utility-Science Utility	0.55	72.17	0.55	72.17	0.55	22.50	0.56	(0.007)	0.54	0.57	0.56	(0.007)	0.54	0.57
Math Utility-Science Self-efficacy	0.23	26.04	0.23	26.04	0.24	12.52	0.23	(0.008)	0.21	0.24	0.23	(0.008)	0.21	0.24
Math Utility-Science Interest	0.27	29.90	0.27	29.90	0.26	12.06	0.27	(0.009)	0.25	0.29	0.27	(0.009)	0.25	0.29
Math Self-efficacy-Science Identity	0.22	28.22	0.22	28.22	0.22	12.09	0.22	(0.008)	0.21	0.24	0.22	(0.008)	0.21	0.24
Math Self-efficacy-Science Utility	0.25	29.38	0.25	29.38	0.26	12.08	0.26	(0.009)	0.24	0.27	0.26	(0.009)	0.24	0.27
Math Self-efficacy-Science Self-efficacy	0.45	64.22	0.45	64.22	0.45	25.56	0.45	(0.006)	0.43	0.46	0.45	(0.006)	0.43	0.46
Math Self-efficacy-Science Interest	0.20	23.18	0.20	23.18	0.20	8.04	0.20	(0.009)	0.18	0.21	0.20	(0.009)	0.18	0.21
Math Interest-Science Identity	0.18	20.41	0.18	20.41	0.18	11.83	0.17	(0.008)	0.16	0.19	0.17	(0.008)	0.16	0.19
Math Interest-Science Utiltiy	0.33	36.44	0.33	36.44	0.35	17.03	0.33	(0.009)	0.32	0.35	0.33	(0.009)	0.32	0.35
Math Interest-Secience Self-efficacy	0.23	26.58	0.23	26.58	0.25	13.68	0.23	(0.009)	0.21	0.25	0.23	(0.009)	0.21	0.25
Math Interest-Science Interest	0.34	38.37	0.34	38.37	0.38	15.45	0.34	(0.010)	0.32	0.35	0.34	(0.010)	0.32	0.35
Factor-Outcome														
Math Identity	**0.26**	21.36	**0.24**	21.08	**0.23**	8.74	**0.26**	(0.013)	0.24	0.28	**0.24**	(0.012)	0.22	0.27
Math Utility	**-0.21**	-14.78	**-0.19**	-14.70	**-0.19**	-6.75	**-0.20**	(0.013)	-0.23	-0.18	**-0.19**	(0.012)	-0.21	-0.17
Math Self-efficacy	**0.13**	9.51	**0.12**	9.49	**0.12**	5.09	**0.13**	(0.013)	0.11	0.16	**0.13**	(0.012)	0.11	0.15
Math Interst	**0.07**	4.87	**0.07**	4.87	**0.06**	2.35	**0.06**	(0.014)	0.04	0.09	**0.06**	(0.013)	0.03	0.08
Science Identity	**0.08**	6.27	**0.07**	6.26	**0.07**	2.97	**0.07**	(0.012)	0.05	0.10	**0.07**	(0.011)	0.05	0.09
Science Utility	**0.04**	2.44	**0.04**	2.43	0.00	0.13	**0.04**	(0.016)	0.01	0.07	**0.04**	(0.015)	0.01	0.07
Science Self-efficacy	**0.09**	6.51	**0.08**	6.51	**0.08**	3.51	**0.09**	(0.013)	0.06	0.11	**0.08**	(0.012)	0.06	0.10
Science Interest	-0.02	-1.33	-0.02	-1.33	-0.01	-0.50	-0.01	(0.014)	-0.04	0.01	-0.01	(0.013)	-0.04	0.01
R^2			0.19				0.18						0.19	

Note: Bayesian significance test based on a one-tailed p-value.

STEM Career.

The first set of columns in Table 13 provides the results of the STEM Career outcome model using WLSMV estimation without weights. Recall that the outcome variable STEM Career is a binary variable indicating perceived STEM career at age 30: Yes=1, No=0. As such, this model employed WLSMV estimation. ML estimation was attempted; however, the model was too complex to converge. The binary interest items for both math and science were added back into the model. Looking at the bottom of Table 13, results showed that only four factors uniquely significantly predicted the outcome: Math Identity, Math Interest, Science Identity, and Science Utility. Science Utility was the strongest predictor with an unstandardized loading of 0.16, while Math Interest was the weakest predictor with an unstandardized loading of 0.08.

Table 13.

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM Career by Various Estimation Methods

	STEM Career													
	WLSMV Est No Weights				WLSMV Est		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
First Order Factor-Measure														
Math Identity-MID1	0.94	332.97	2.65	41.39	2.40	13.05	0.94	(0.004)	0.93	0.95	2.83	(0.102)	2.61	2.97
Math Identity-MID2	0.86	275.78	1.66	73.23	1.65	28.30	0.86	(0.004)	0.85	0.87	1.67	(0.029)	1.62	1.73
Math Utility-MUT1	0.74	150.10	1.10	68.22	1.12	28.95	0.75	(0.005)	0.74	0.76	1.14	(0.017)	1.10	1.17
Math Utility-MUT2	0.84	173.91	1.58	49.98	1.60	19.30	0.82	(0.004)	0.81	0.83	1.44	(0.024)	1.40	1.49
Math Utility-MUT3	0.86	201.92	1.70	52.12	1.68	18.39	0.89	(0.003)	0.88	0.90	1.95	(0.036)	1.88	2.03
Math Self-efficacy-MSE1	0.90	427.00	2.05	82.29	2.18	23.59	0.90	(0.002)	0.90	0.91	2.07	(0.028)	2.02	2.13
Math Self-efficacy-MSE2	0.85	319.30	1.59	90.52	1.56	37.43	0.85	(0.003)	0.85	0.86	1.64	(0.022)	1.59	1.68
Math Self-efficacy-MSE3	0.90	427.14	2.05	82.40	2.01	23.13	0.90	(0.003)	0.89	0.90	2.03	(0.030)	1.97	2.09
Math Self-efficacy-MSE4	0.91	455.46	2.23	76.49	2.39	23.24	0.91	(0.002)	0.91	0.92	2.19	(0.033)	2.13	2.26
Math Interest-MIN1	0.87	228.71	1.77	55.13	2.08	17.55	0.86	(0.004)	0.85	0.87	1.68	(0.028)	1.62	1.73
Math Interest-MIN2	0.71	136.56	1.00	68.53	0.97	23.50	0.68	(0.005)	0.67	0.69	0.92	(0.013)	0.89	0.94
Math Interest-MIN3	0.70	147.57	0.97	76.21	0.98	27.77	0.71	(0.005)	0.70	0.72	1.02	(0.015)	0.99	1.05
Math Interest-MIN4 (binary)	0.62	64.43	0.79	39.77	0.78	19.16	0.66	(0.008)	0.64	0.67	0.87	(0.019)	0.83	0.90
Math Interest-MIN5 (binary)	0.70	93.39	0.99	47.11	0.87	20.09	0.72	(0.007)	0.71	0.73	1.04	(0.021)	1.00	1.08
Math Interest-MIN6 (binary)	0.77	94.66	1.21	38.36	1.25	16.43	0.69	(0.007)	0.68	0.71	0.96	(0.019)	0.92	1.00
Science Identity-SID1	0.93	275.97	2.52	37.43	2.44	9.82	0.94	(0.003)	0.93	0.94	2.66	(0.075)	2.54	2.82
Science Identity-SID2	0.86	241.39	1.70	61.92	1.66	20.44	0.86	(0.004)	0.86	0.87	1.70	(0.027)	1.64	1.75
Science Utility-SUT1	0.73	140.57	1.07	65.25	1.14	23.66	0.71	(0.005)	0.70	0.72	1.00	(0.015)	0.97	1.03
Science Utility-SUT2	0.80	165.79	1.35	58.55	1.36	21.08	0.80	(0.005)	0.79	0.81	1.34	(0.023)	1.30	1.39
Science Utility-SUT3	0.80	182.83	1.35	64.87	1.26	23.95	0.84	(0.005)	0.83	0.84	1.52	(0.027)	1.47	1.57
Science Self-efficacy-SSE1	0.88	344.28	1.82	79.86	1.78	25.01	0.88	(0.003)	0.87	0.88	1.83	(0.028)	1.78	1.89
Science Self-efficacy-SSE2	0.83	266.12	1.49	82.77	1.43	28.95	0.84	(0.003)	0.83	0.85	1.54	(0.021)	1.50	1.58
Science Self-efficacy-SSE3	0.89	374.29	1.97	76.51	1.96	21.51	0.89	(0.003)	0.89	0.90	1.96	(0.033)	1.90	2.02
Science Self-efficacy-SSE4	0.88	334.78	1.88	73.67	1.95	21.95	0.88	(0.003)	0.87	0.89	1.84	(0.029)	1.79	1.90
Science Interest-SIN1	0.87	239.46	1.79	56.77	1.86	24.34	0.86	(0.004)	0.86	0.87	1.70	(0.029)	1.65	1.76
Science Interest-SIN2	0.79	183.91	1.29	68.92	1.29	25.02	0.78	(0.005)	0.77	0.79	1.23	(0.019)	1.20	1.27
Science Interest-SIN3	0.74	171.25	1.11	76.79	1.12	28.61	0.77	(0.005)	0.76	0.78	1.20	(0.017)	1.17	1.23
Science Interest-SIN4 (binary)	0.61	53.02	0.78	33.08	0.72	16.53	0.61	(0.010)	0.59	0.63	0.78	(0.021)	0.73	0.81
Science Interest-SIN5 (binary)	0.59	62.47	0.73	40.77	0.70	18.28	0.63	(0.008)	0.62	0.65	0.82	(0.018)	0.79	0.85
Science Interest-SIN6 (binary)	0.76	86.02	1.17	36.34	1.12	19.11	0.64	(0.008)	0.63	0.66	0.84	(0.019)	0.80	0.88

Table 13 continued.

Unstandardized and Standardized Path Coefficients and Test Statistics for Outcome STEM Career by Various Estimation Methods

	STEM Career													
	WLSMV Est No Weights				WLSMV Est		Bayesian Est No Weights							
	Standardized		Unstandardized		Unstandardized		Standardized				Unstandardized			
Relationship	Path	Z	Path	Z	Path	Z	Path	(SD)	95% CI		Path	(SD)	95% CI	
First Order Factor intercorrelations														
Math Identity-Math Utility	0.39	50.81	0.39	50.81	0.38	20.04	0.40	(0.008)	0.38	0.41	0.40	(0.008)	0.38	0.41
Math Identity-Math Self-efficacy	0.69	139.83	0.69	139.83	0.68	46.14	0.69	(0.005)	0.68	0.70	0.69	(0.005)	0.68	0.70
Math Identity-Math Interest	0.71	144.55	0.71	144.55	0.71	71.29	0.70	(0.006)	0.69	0.71	0.70	(0.006)	0.69	0.71
Math Utility-Math Self-efficacy	0.45	62.64	0.45	62.64	0.44	21.33	0.44	(0.008)	0.43	0.46	0.44	(0.008)	0.43	0.46
Math Utility-Math Interest	0.57	89.12	0.57	89.12	0.56	35.95	0.55	(0.007)	0.54	0.57	0.55	(0.007)	0.54	0.57
Math Self-efficacy-Math Interest	0.65	128.65	0.65	128.65	0.64	48.77	0.66	(0.006)	0.65	0.67	0.66	(0.006)	0.65	0.67
Science Identity-Science Utility	0.53	73.00	0.53	73.00	0.53	26.47	0.53	(0.008)	0.51	0.54	0.53	(0.008)	0.51	0.54
Science Identity-Science Self-efficacy	0.61	103.10	0.61	103.10	0.60	45.29	0.61	(0.006)	0.60	0.62	0.61	(0.006)	0.60	0.62
Science Identity-Science Interest	0.63	111.66	0.63	111.66	0.63	34.95	0.61	(0.007)	0.60	0.62	0.61	(0.007)	0.60	0.62
Science Utility-Science Self-efficacy	0.51	71.24	0.51	71.24	0.52	36.04	0.50	(0.008)	0.48	0.51	0.50	(0.008)	0.48	0.51
Science Utility-Science Interest	0.65	110.77	0.65	110.77	0.66	37.17	0.64	(0.007)	0.62	0.65	0.64	(0.007)	0.62	0.65
Science Self-efficacy-Science interest	0.63	113.59	0.63	113.59	0.62	45.49	0.63	(0.006)	0.61	0.64	0.63	(0.006)	0.61	0.64
Math Identity-Science Identity	0.36	50.75	0.36	50.75	0.36	21.61	0.31	(0.008)	0.30	0.33	0.31	(0.008)	0.30	0.33
Math Identity-Science Utility	0.26	29.24	0.26	29.24	0.26	13.39	0.24	(0.009)	0.22	0.26	0.24	(0.009)	0.22	0.26
Math Identity- Science Self-efficacy	0.32	41.38	0.32	41.38	0.33	17.85	0.30	(0.008)	0.29	0.32	0.30	(0.008)	0.29	0.32
Math Identity-Science Interest	0.18	20.92	0.18	20.92	0.20	11.99	0.17	(0.009)	0.15	0.18	0.17	(0.009)	0.15	0.18
Math Utility-Science Identity	0.15	17.57	0.15	17.57	0.17	9.05	0.15	(0.009)	0.13	0.16	0.15	(0.009)	0.13	0.16
Math Utility-Science Utility	0.59	79.81	0.59	79.81	0.60	25.74	0.56	(0.008)	0.55	0.58	0.56	(0.008)	0.55	0.58
Math Utility-Science Self-efficacy	0.24	27.26	0.24	27.26	0.25	13.76	0.23	(0.009)	0.21	0.25	0.23	(0.009)	0.21	0.25
Math Utility-Science Interest	0.26	28.97	0.26	28.97	0.26	12.21	0.25	(0.009)	0.23	0.27	0.25	(0.009)	0.23	0.27
Math Self-efficacy-Science Identity	0.24	30.46	0.24	30.46	0.24	12.96	0.23	(0.008)	0.21	0.24	0.23	(0.008)	0.21	0.24
Math Self-efficacy-Science Utility	0.27	30.56	0.27	30.56	0.28	12.14	0.26	(0.009)	0.24	0.27	0.26	(0.009)	0.24	0.27
Math Self-efficacy-Science Self-efficacy	0.47	68.57	0.47	68.57	0.48	27.67	0.46	(0.007)	0.45	0.48	0.46	(0.007)	0.45	0.48
Math Self-efficacy-Science Interest	0.19	22.22	0.19	22.22	0.19	7.95	0.18	(0.009)	0.17	0.20	0.18	(0.009)	0.17	0.20
Math Interest-Science Identity	0.15	18.79	0.15	18.79	0.16	11.08	0.15	(0.009)	0.13	0.16	0.15	(0.009)	0.13	0.16
Math Interest-Science Utiltiy	0.31	35.17	0.31	35.17	0.31	16.27	0.29	(0.009)	0.27	0.30	0.29	(0.009)	0.27	0.30
Math Interest-Secience Self-efficacy	0.22	25.39	0.22	25.39	0.23	12.54	0.21	(0.009)	0.19	0.22	0.21	(0.009)	0.19	0.22
Math Interest-Science Interest	0.27	31.89	0.27	31.89	0.30	12.98	0.22	(0.009)	0.21	0.24	0.22	(0.009)	0.21	0.24
First Order Factor-Outcome														
Math Identity	**0.08**	3.31	**0.09**	3.31	0.00	0.05	**0.08**	(0.021)	0.04	0.12	**0.09**	(0.022)	0.04	0.13
Math Utility	-0.04	-1.64	-0.04	-1.64	-0.04	-0.89	-0.03	(0.021)	-0.07	0.01	-0.03	(0.022)	-0.07	0.01
Math Self-efficacy	-0.03	-1.12	-0.03	-1.12	-0.05	-1.05	-0.01	(0.022)	-0.06	0.03	-0.01	(0.023)	-0.06	0.03
Math Interst	**0.08**	2.82	**0.08**	2.81	**0.18**	2.84	**0.07**	(0.023)	0.02	0.11	**0.07**	(0.024)	0.02	0.12
Science Identity	**0.14**	6.73	**0.15**	6.70	**0.19**	4.83	**0.14**	(0.018)	0.10	0.17	**0.14**	(0.019)	0.11	0.18
Science Utility	**0.16**	5.67	**0.16**	5.62	0.07	1.02	**0.16**	(0.025)	0.11	0.21	**0.16**	(0.026)	0.12	0.22
Science Self-efficacy	-0.01	-0.26	-0.01	-0.26	0.02	0.43	-0.01	(0.021)	-0.05	0.03	-0.01	(0.022)	-0.06	0.03
Science Interest	-0.04	-1.44	-0.04	-1.43	-0.05	-0.83	-0.04	(0.022)	-0.08	0.01	-0.04	(0.023)	-0.09	0.01
R^2		0.08			0.06				0.08					

Note: Bayesian significance test based on a one-tailed p-value.

Male/Female invariance.

Invariance tests were conducted to determine if the relationships between motivation subconstructs and STEM outcomes were invariant between males and females, before weights were included in the models. For the purposes of this study, only configural and metric invariance were of interest. Preliminary analyses found configural invariance across groups. That is, for both males and females a first order model with all factors correlated (Model 4a) was the best fitting model. Once configural invariance was established, metric invariance was tested for the three outcome models. Traditionally, measurement invariance has been defined by changes in χ^2 ($\Delta\chi^2$) between nested models (groups constrained to be equal vs. groups free to vary). However, research shows that χ^2 tests are affected by sample size and thus with large samples a small discrepancy may lead to an increase in Type I error (i.e. concluding non-invariance when the model is in fact invariant) (Chen, 2007; Sass, Schmitt, & Marsh, 2014). Chen (2007) shows that alternative fit-indices such as ΔCFI, ΔRMSEA, and ΔSRMR provide better criteria for evaluating measurement invariance. Chen specifically recommended these criteria: "for testing loading invariance a change of ≤-.005 in CFI, supplemented by a change of ≥.010 in RMSEA or a change of ≥.025 in SRMR would indicate non-invariance" (p. 501).

Results (provided in Table 14) showed that each of the three outcome models were invariant across males and females. The $\Delta\chi^2$ test statistic was significant across all three models, however the large sample size makes this result suspect. The alternative fit indices, using Chen's (2007) recommended cutoff values, indicate invariance. In other words, males and females were estimated to have similar achievement-motivation subconstruct relationships.

Table 14.

Measurement Invariance across gender

	Number Parameters Estimated	*Without Weights*								
		Model fit for constrained model					*Results of model comparison*			
		χ^2	(df)	CFI	TLI	RMSEA	$\Delta\chi2$	(df)	ΔCFI	ΔRMSEA
STEM Credits	164	15781.60	536	0.935	0.928	0.049	23.61	8	0.000	-0.001
STEM GPA	164	16054.12	536	0.935	0.927	0.050	21.73	8	0.000	0.000
STEM Career	228	31836.09	860	0.952	0.948	0.056	265.02	22	0.001	-0.001

Weights

Next, the complex survey weights were added to each of the outcome models (*Mplus* input code available upon request). The complex survey weights accounted for the nested structure of the data, nonresponse, and uneven sampling. Including the complex sampling weights is necessary to correctly calculate the standard errors. Incorrectly leaving out the survey weights in the model "can lead to estimated variances and confidence intervals that are too small, which may lead to incorrect results from hypothesis tests" (Ingels et al., 2015, p. 124). It is expected that results will change based on this more correct estimation of the models.

STEM credits with weights.

The second set of columns in Table 11 provides the unstandardized results of the STEM credits outcome model using ML estimation and complex survey weights (only the unstandardized results are given, because standard errors and significance tests are not available for standardized loadings when weights are included in the model in *Mplus*). Again, we see that all path estimates between the indicators and factors were significant and similar to the estimates in the unweighted model. The factor correlations were also nearly identical to the unweighted model. Therefore, the measurement aspect of the model was not greatly affected by the addition of the survey weights. The results from the structural component of the model did change however. We see now that only Math Identity, Science Identity, Math Self-efficacy, and Science

Self-efficacy were significant predictors of STEM Credits earned. Also, the finding of Math Utility being a significant negative predictor from the unweighted model, is now non-significant.

STEM GPA with weights.

The second set of columns in Table 12 provides the unstandardized results of the STEM GPA outcome model using ML estimation and complex survey weights. Again we see that results from the measurement portion of the model (indicator to factor loadings, and factor correlations) did not change in any substantive way. Results from the structural component of the model (factor to outcome loadings) did change after including survey weights. Science Utility, which was the weakest significant predictor in the unweighted model, became non-significant in the weighted model. All other results are consistent with the unweighted model: Math Identity was the strongest predictor and Math Utility continues to be a significant negative predictor of STEM GPA, providing more evidence for a possible suppressor effect.

One indication of negative suppression is when independent variables are positively correlated with the dependent variable and positively correlated with each other, but one of them receives a negative regression weight when they are all included in the model (Maassen, & Bakker, 2001). This is the case for the math utility factor, where it has a positive zero-order correlation with STEM GPA, and positive correlations with the other factors, but received a negative weight in the model. Conger (1974) defines a suppressor variable as "a variable that increases the predictive validity of another variable (or set of variables) by its inclusion in a regression equation" (p. 36; as quoted in Maassen, & Bakker, 2001, p. 246). Stated another way, a suppressor variable is one which "suppresses variance that is irrelevant to prediction of the dependent variable based on its correlations the other independent variables" (Tabachnick & Fidell, 1996, p. 165). Using this definition, follow-up analyses showed that math identity, math

self-efficacy, math interest, science utility, and science interest are all individually and in combination suppressor variables for math utility. Maassen and Bakker (2001) discuss suppressor variables in the context of path models, and they conclude by stating:

> If a variable has been designated as the suppressor, and a path coefficient between this variable and the dependent variable has been found with a sign opposite to that hypothesized, one should not then conclude that a direct effect contrary to that expected is operating. A variable only appears as a suppressor in combination with one or more other explanatory variables (Maassen, & Bakker, 2001, p. 268).

This means that after accounting for the other factors in the model, the unique information left over in math utility is negatively predictive of STEM GPA. As Maassen and Bakker (2001) note, this is not the same as saying that math utility is uniquely negatively predictive of STEM GPA. When suppressor effects are present, the variable, or in this case, factor being suppressed (math utility), should not be interpreted as a direct effect. Only with the other factors in the model, is math utility uniquely negatively predictive of STEM GPA. This can be thought of as similar to an interaction effect, as opposed to a direct effect.

STEM Career with Weights.

Lastly, the second set of columns in Table 13 provides the unstandardized results of the STEM Career outcome model using WLSMV estimation and complex survey weights. Just as in the previous two models, the measurement portion of the model did not have any substantive changes. Results from the structural portion of the model did change. Now, only Math Interest and Science Identity were significant predictors of perceived STEM Career at age 30, with paths of 0.18 and 0.19 respectively.

Male/Female invariance with weights included.

Male/female invariance was tested again after weights were included in the model (see Table 15). Preliminary results again showed configural invariance. When using replicate weights

in *Mplus*, the χ^2 test statistic is not provided, nor is the RMSEA provided for WLSMV models. To test metric invariance for the STEM Credits and STEM GPA models, ΔRSMEA and ΔSRMR were assessed. Using Chen's (2007) recommended cutoff values we see that both the STEM Credits and STEM GPA models are invariant across males and females. The only test statistic provided for WLSMV estimated models is WRMR. This statistic is problematic however, because it is considered to be experimental. Sass, Schmitt, and Marsh (2014) show that ΔWRMR produces inflated Type I error rates and they conclude that this statistic should not be used as an alternative fit index to detect invariance. This is problematic since the only test statistic provided by *Mplus* when using WLSMV estimation and replicate weights, is WRMR. Sass, Schmitt, and Marsh provide some guidance in that they chose a cutoff criteria of ΔWRMR ≥0.50 based on preliminary analyses explored in their study. Although they state that this criterion may need to be altered, my result of ΔWRMR=0.042 was so far below the criteria used by Sass, Schmitt, and Marsh that there may be potential evidence for male/female invariance.

Table 15.
Weighted Measurement Invariance Across Gender

	Weights				
	Model fit for constrained model			*Results of model comparison*	
	#Free Parameters	RMSEA	SRMR/WRMR	ΔRMSEA	ΔSRMR/WRMR
STEM Credits	156	0.053	0.034	0.001	0.000
STEM GPA	156	0.054	0.034	0.000	0.000
STEM Career	220	--	3.859	--	0.042

Note: Chi-square test statistic is not available when using replicate weights.

Summary of ML and WLSMV Results

A first order model with all factors correlated (Model 4a) was found to be the best fitting model. This model met configural invariance across males and females. That is, for both males only and females only model 4a was still the best fitting model. When complex survey weights were included in the model the measurement portion of the model did not change in any substantive way, however the structural component did, with fewer factors being significant in

the weighted model, than the unweighted model. Science Identity was the only factor found to be significantly predictive of all three outcomes in the weighted models.

Bayesian Estimation

Lastly, Bayesian estimation was conducted to provide an example of an alternative estimation method and determine if the relationships found using frequentist methods would change when using a Bayesian approach. Recall from Chapter 5 that Bayesian and frequentist results converge as sample size increases. Therefore, with the large survey sample size, it was hypothesized that the results will not change in any substantive way. However, there may be other advantages to using Bayesian methods when analyzing complex survey data, which will be discussed. Standardized and unstandardized results are provided in the third set of columns for each of the outcomes in Tables 11, 12, and 13. Results show that for each of the models, the results do not change in any substantive way. Path coefficients between the factors and the outcome are within one one-hundredth of a point, and factors identified as significant stayed the same. Only the unweighted estimates are provided for the Bayesian analyses because at this time, there is no statistically sound way to use complex survey weights with Bayesian analyses, however this is an active area of research (see: Little, 2003; Rao, 2011; Si, Pillai, & Gelman, 2015). The benefit to using Bayesian analyses when you have a large sample size, is in the interpretation of results. For example, in the STEM Credits outcome model, both the unweighted frequentist and Bayesian path coefficient between Math Identity and the outcome is 0.34 and significant. The frequentist interpretation of this result is that over an infinite number of trials, this coefficient is rare enough to be considered to be from a different population than one where the coefficient is 0. Therefore, the coefficient of 0.34 was accepted as our best estimate of the parameter and that again, over an infinite number of trials, 95% of our confidence intervals

would contain the parameter. The Bayesian interpretation is that there is a 95% probability that the parameter lies within the credibility interval of 0.26 and 0.39, with 0.34 being the most likely value among this range.

In summary, Bayesian findings were not substantively different from the frequentist results. A benefit to using Bayesian analysis is in the ease and intuitive nature of interpreting the results, however a critical limitation to Bayesian analyses of complex survey data is in the inability to model the complex survey weights, which in the frequentist analyses were found to substantively change the results in the structural portion of the model.

Chapter 8: Discussion and Conclusions

The most recent U.S. National Science Foundation report on women, minorities, and persons with disabilities in science and engineering (2015) shows that the well-known gender gap in science, technology, engineering and math (STEM) fields continues to persist and yet the urgent need for a STEM-educated workforce grows. Thus, research in the area of STEM achievement motivation is one avenue for potentially understanding and intervening in the gender gap. Findings from present study contribute to the literature by: 1) investigating the relationships between grade 9 motivational subconstructs (e.g., identity with the subject matter, and interest in the subject matter) in relation to the larger construct of motivation within the specific domains of math and science; 2) testing whether those motivational variables are related to end of high school STEM outcomes, including course credits earned, GPA, and STEM career aspirations; and 3) testing whether the relationships between STEM motivation variables and STEM outcomes are moderated by gender (in other words, are relationships stronger or weaker for females compared to males?). In addition to investigating these substantive research questions, the present study also compared model estimates from Maximum Likelihood (ML), Weighted Least Squares Minimum Variance (WLSMV), and Bayesian estimators of each of the structural equation models, with and without use of complex sample survey weights.

Research Question 1: What is the nature of STEM Motivation?

The first research question tested the relationship between motivation subconstructs, identity, utility, self-efficacy, and interest for the domains math and science, and in this process, evaluated the evidence for the presence of a second-order factor structure. Model 1-4 results showed that there was no evidence for a second order factor structure, and that the best fitting model is one in which all first order factors are free to correlate (Model 4a; see Figure 7).

After establishing the best fitting model, we found that, although all the subconstructs were positively correlated with each other, correlations were highest within a given domain. Within the math domain, identity and self-efficacy had the highest correlation at 0.66, and within the science domain, utility and interest had the highest correlation at 0.62. This different correlational pattern provides evidence for the domain specificity of motivation constructs. Across domains, each construct was most highly correlated with its like construct; the two highest correlations across domains were between math utility and science utility at 0.55, and math self-efficacy and science self-efficacy at 0.45. Of all the pairings, math interest and science identity had the lowest correlation with each other, at 0.18.

There is a paucity of research on the relationship between cross-theoretical motivation constructs (Bathgate, Schunn, & Correnti, 2013). This study adds directly to the literature by showing that the cross-theory motivation constructs of identity, utility, self-efficacy, and interest measured related but distinct motivation constructs, and that each was specific to either Math or Science. This domain specific finding is consistent with previous research on motivation and domain specificity (Bong, 2001; Bong, Cho, Ahn, & Kim, 2012; Jansen, Scherer, & Schroeders, 2015; Scherer, 2013).

Research Question 2: What is the Relationship of STEM Motivation with Outcomes?

Research question 2 asked: Do 9th grade math and science motivation constructs each uniquely predict three STEM outcomes, which included course credits, GPA, and STEM career aspiration? The present study's results indicate that each domain specific construct was positively, significantly predictive of each outcome when tested as individual predictors of STEM outcomes. However, when all motivation subconstructs were included in the model, the results show that not all motivation constructs were uniquely predictive, and for those that were,

the findings were not entirely consistent across the three STEM outcomes. The two consistent findings however included the result that science utility was not uniquely predictive of any of the outcomes, while science identity was the only factor uniquely predictive of all three outcomes.

Research Question 3: Are Relationships among STEM Motivation and Outcome Variables Moderated by Gender?

Overall, the findings of the present study show that there was no evidence of differences among males and females on relationships between the STEM motivation constructs and outcomes. On the surface this might appear to be incongruent with much of the STEM motivation research, in particular, the research discussed in Chapter 3. Recall however that the invariance tests we conducted were not on *mean* differences between males and females, but rather on the relationship estimates (loadings) among variables in the models. In other words, the first-order model with all factors correlated fit best for both males and females, and the relationships among the motivation constructs and STEM outcomes were the same for males and females. *This is not the same as saying that males and females have the same STEM outcomes.*

This finding is actually consistent with Marsh, Trautwein, Ludtke, Koller, and Baumert (2005) who studied the relationships between self-concept, interest, and achievement, also using a structural equation modeling approach. Similar to the present study, the authors tested the invariance of path coefficient estimates across males and females and found the model to be invariant. However, the authors also tested invariance of latent variable *mean* differences and found that males scored significantly higher on math self-concept and math interest than females. In sum, although there were male/female differences in means, the relationships among the motivation and achievement variables were the same. Another study also found similar results: Frenzel, Pekrun, and Goetz (2007) studied male/female differences in control, value beliefs, and

emotions in math. Mean differences in emotions were discovered, with females reporting significantly less enjoyment and pride in math than males, and significantly more on math anxiety, hopelessness, and shame. Nevertheless, the structural relationships among the variables were not found to be dissimilar among males and females.

Again, both the prior and current research has shown that even though males and females might differ on mean levels of motivation and feelings around STEM, the underlying relationships between the constructs and outcomes functioned similarly. As can be seen in Table 16, which provides the weighted meansand *t*-test results of each motivation subconstruct for males and females, males did score significantly higher on all but three of the motivation subconstructs, although the effect sizes were quite small (Cohen's *d*s < .25).

Table 16.
Weighted Disagreggated Descriptive Statistics and t-tests for Math & Science Motivation Subconstructs

	Male			*Female*			*Males vs. Females*		
Factor	*N*	*M*	*(SD)*	*N*	*M*	*(SD)*	*t*	*p*	*d*
Math Identity	7551	2.57	(0.86)	7637	2.48	(0.86)	106.23	<.001 *	0.10
Math Utility	7551	3.18	(0.63)	7637	3.15	(0.61)	43.43	<.001 *	0.05
Math Self-efficacy	7551	3.00	(0.66)	7637	2.87	(0.65)	185.52	<.001 *	0.20
Math Interest	7551	1.48	(0.57)	7637	1.52	(0.55)	-81.06	<.001 *	-0.07
Science Identity	7551	2.33	(0.82)	7637	2.27	(0.78)	79.55	<.001 *	0.07
Science Utility	7551	2.91	(0.63)	7637	2.92	(0.61)	-27.77	<.001 *	-0.02
Science Self-efficacy	7551	2.91	(0.63)	7637	2.77	(0.61)	198.20	<.001 *	0.23
Science Interest	7551	1.42	(0.61)	7637	1.42	(0.58)	1.32	0.188	0.00

Note. N based on students with positive weights. Observed *p* -values shown for *t* -tests; asterisk indicates that the *t* -test is significant after adjustment for multiple comparisons (Bonferroni). Cohen's *d* computed as the mean differences divided by the square root of the pooled variance.

It is important to note that previous research shows that *males and females do not have different aptitudes for math and science* (Hyde, Lindberg, Linn, Ellis, & Williams, 2008). Therefore, if STEM potential is the same for males and females, and motivation subconstruct structures and relationships are the same for males and females, then there appears to be external

forces producing the persistent mean differences in STEM motivation levels. The implication of these results might be best understood through the *feminist theory of intersectionality*, which states that gender, sexuality, race, class, nation, and other systems of oppression mutually construct one another to form a "matrix of oppression" that we all live in (Collins, 2000). This matrix of oppression creates disadvantages for those at the bottom of the hierarchy, and unacknowledged benefits for those at the top (Collins, 2000; Johnson, Brown, Carlone, & Cuevas, 2011). This theory recognizes that structures of power, privilege, and oppression are brought to bear on females' motivation experiences in STEM courses.

This is not to say that one motivation subconstruct is more important for females than for males – math and science identity are likely to be equally important for males and females – but rather that current STEM *culture* (e.g., within classrooms, schoosl, textbooks, and media) privileges a male over a female, which directly leads to the oppression of females in STEM and the subsequent "leaking" from the pipeline at all stages. A study by Hoffman (2002) provides some insight: after implementing an intervention to reduce gender bias in a science classroom, females in the intervention classroom had significantly higher interest and achievement than females in the control classroom. This implies that there are external environmental forces at work and this is an important future research area to take up.

Research Question 4: Does Analysis Estimation Choice Matter?

The final research question was centered around whether analysis estimation choice would affect inferences. Three model estimation methods were tested: Maximum Likelihood (ML), Weighted Least Squares Minimum Variance (WLSMV), and Bayesian estimation, and for the first two (frequentist) approaches, models were estimated with and without complex sample survey weights incorporated. Comparing the unweighted models versus the weighted models, we

see that the results (i.e., model-based infernece) did change (see first and second set of columns in Tables 11, 12, 13). This was actually expected since the survey weights account for the nested structure of the data (students within schools and regions of the country), as well as non-response and oversampling. Specifically, the analytic weight accounted for student nonresponse in the base-year, first-follow-up, and the 2013 update; the BRR weights accounted for the complex clustered random sampling design. Including both the analytic and BRR weights ensured optimal estimation of the standard errors. When weights were not included, the number of significant factor-to-outcome paths increased (indicating Type I error inflation). To test the effect of removing the replicate weights in the model, the STEM Credits outcome was analyzed with only the analytic weight. Table 17 provides the side-by-side results of the path loadings for the STEM Credits outcome with both the analytic and replicate weights and the analytic weight only. When replicate weights were removed, there was no substantive difference in path loadings (i.e., no invariance), therefore it is reasonable to assume that the analytic weight plays a positive role in the analysis process.

Table 17.
Unstandardized Path Coefficients for STEM Credits With and Without Replicate Weights.

	RepWeights ML			*No RepWeights* MLR		
Relationship	Path	SE	*p*	Path	SE	*p*
Factor-Outcome						
Math Identity	**0.28**	0.07	<0.001	**0.28**	0.06	<.001
Math Utility	-0.07	0.10	0.51	-0.07	0.07	0.37
Math Self-efficacy	**0.17**	0.07	0.03	**0.17**	0.07	0.02
Math Interst	0.12	0.07	0.10	0.12	0.07	0.08
Science Identity	**0.19**	0.06	0.001	**0.19**	0.06	0.001
Science Utility	-0.06	0.11	0.62	-0.06	0.09	0.55
Science Self-efficacy	**0.17**	0.07	0.01	**0.17**	0.06	0.01
Science Interest	0.03	0.07	0.67	0.03	0.07	0.68
R^2	0.07			0.07		

Note. It was necessary to use MLR estimation in Mplus when only the analytic weight was included in the model.

Comparing the frequentist versus Bayesian unweighted models (recall that weights could not be included in the Bayesian analyses), we saw that substantive results did not change. Significant paths in the frequentist models were the same as those in the Bayesian models, and the majority of the loading estimates were within one one-hundredth of a point of each other. This result was as expected, since as sample size increases, Bayesian and frequentist results converge. Importantly, although path coefficient results were similar, the inferences about them would be slightly different in meaning. In the Bayesian analyses, one is able to make probabilistic statements about the parameters, but in the frequentist analyses, one makes probabilistic statements about the sample estimates.

Limitations

As with any study, there are limitations. First, due to the complex nature of the analyses, some variables were not included in the models (such as SES, ethnicity, and whether or not a parent is in a STEM field) even if prior research has shown some of these variables are quite

related to math and science motivation and achievement (Alexander, 2015; Barr, 2015; Fajardo, 205; Middleton, 2013). More importantly perhaps is that, due to the use of an extant dataset, some of the theoretical motivation subconstructs are not fully measured by the observed variables in the models, particularly in the case of the interest and identity items. The interest items relate most closely to only the first phase of Hidi and Renninger's (2006) 4-phase model of interest development where interest is characterized as affect or liking. The identity items in the present study could be capturing a broad range of student characteristics such as student achievement, which may impact how a person responds to seeing themselves or others as a math or science person. Further, some variables were included in one wave but not another. For example, the HSLS:09 wave 3 did not measure information on students' college admissions or post-high school job (and whether or not they entered a STEM field). A final limitation that should be noted is that there is a large proportion of variance in the three outcomes that was not explained; clearly, motivation is not alone in affecting STEM outcomes; it is likely that context variables matter a great deal (e.g., demographics, school and district curricula policies, as well as classroom cultural norms). Nevertheless, the present analysis was able to test and incorporate a rich variety of STEM motivation items that clearly formed a coherent structure in our models and were predictive of key STEM outcomes.

Conclusion

Statistical.

Many methodological options are available to a researcher interested in analyzing complex survey data using a structural equation modeling framework. The following are some challenges encountered and recommendations. The first recommendation is to use ML estimation when possible because it was by far the most flexible estimation method compared to WLSMV

and Bayesian estimation processes. In particular, ML allowed for the incorporation of complex sample survey weights that are necessary to prevent Type I error inflation. Further, ML estimation also allowed for invariance testing with survey weights included in the model and provided a rich set of model fit indices for ease of relative model fit comparison.

WLSVM estimation was the next best. It allowed for the inclusion of survey weights, but it is not recommended if the researcher is interested in conducting invariance tests. The only test statistic provided with WLSMV estimation when conducting invariance testing was the WRMR, which is still experimental in its use, and has been found to be unreliable in some cases (Sass, Schmitt, & Marsh, 2014). Howver, WLSMV estimation is the only option in certain situations, such as when analyzing a binary outcome. If invariance testing is a main research question, then it is recommended that the researcher use IRT methods instead for invariance testing (see Millsap, 2011; Sass, Schmitt, & Marsh, 2014).

Lastly, Bayesian estimation was the least flexible method for analyzing complex survey data. The unweighted data could be analyzed, but statistically sound methods of including survey weights in Bayesian models do not yet exist, although it is an active area for future research. If a researcher is determined to use Bayesian analysis to analyze complex survey data, then it will be necessary to obtain a restricted dataset which includes the primary sampling units (PSUs) which will be needed to account for the nested sampling design. The researcher will also need to account for non-response. Obtaining a restricted dataset can be time consuming and involves many procedures for ensuring confidentiality of the data. Due to all of these challenges, Bayesian analysis of complex survey data is not recommended, until survey weights can be more easily included in the model.

Substantive.

This study's results show that motivation subconstructs were measuring related but distinct constructs, and that they are domain-specific. Moreover, the relationships between the constructs were invariant across males and females. Math identity, math self-efficacy, science identity, and science self-efficacy each significantly uniquely predicted the number of STEM credits earned by the end of high school. Math identity, math self-efficacy, math interest, science identity, and science self-efficacy each significantly uniquely predicted STEM GPA at the end of high school. Math utility was found to be a significant negative predictor of STEM GPA due to a suppressor effect from all but two of the other factors – the unique variance left over in math utility was negatively predictive of STEM GPA. Together, these findings show the domain-specific nature of motivation constructs as well as their outcome-specific nature. Six of the eight constructs uniquely predicted STEM GPA while only two uniquely predicted STEM career.

Perhaps the most salient finding is that science identity was predictive of all three outcomes and therefore may be a more general STEM predictor than the other constructs. As such, it is suggested that intervention researchers interested in broadening their STEM impact may look to increasing students' science identity. Interestingly, although science identity was predictive of all three outcomes, it was only significant predictor of STEM career. Further, math identity was the strongest predictor for both the STEM credits and STEM GPA. Intervention researchers interested in maximizing their STEM impact, may look to increasing students' math identity. Clearly math and science identity are key constructs in predicting STEM outcomes. Further, because females were significantly lower than males on their mean science identity (d = -.07; also on math identity: d = -.10) it would appear that future research should focus on the environmental contexts affecting females' STEM identities in particular.

This said, that although math and science identity were strongly predictive of the three STEM outcomes studied, this is not to say that intervention efforts related to the other motivation subconstructs should be abandoned. Each subconstruct was individually predictive of the STEM outcomes studied, and therefore also useful points of intervention. Moreover, research that investigates and compares one or more combinations of subconstructs may be quite fruitful. In the present study, the motivation subsconstructs together accounted for 18% of the variation in GPA (weighted, ML model) (and this is without factoring in demographic variables). In other words, we don't have to throw everything at the wall and hope something sticks. It is suggested that interventions related to increasing STEM course enrollment target math and science identity and self-efficacy; interventions related to STEM achievement target in particular math identity and math self-efficacy while also potentially including math interest, science identity and science self-efficacy. Lastly, it is suggested that interventions related to STEM career aspirations target math interest and science identity. These suggestions hold true for both males and females.

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Appendix: *Mplus* Input Instructions

Model 1a

```
Title: First Order CFA 1F Math ML Estimation Items standardized. Intercepts
0. No MFAVSUBJ MLESTSUB MENJOYS
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-
6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 !Zscore items before setting intercepts to 0
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS

 Model: MMotivation BY MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL
 MENJOYING MWASTE MBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0];
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0

 Output: sampstat stdyx;
```

Model 1b

```
Title: First Order CFA Science 1F ML Estimation Items Standardized Intercepts
0 No SFAVSUBJ SLESTSUB SENJOYS
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-
6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING
 !Removed items SFAVSUBJ SLESTSUB SENJOYS;
 !Zscore items before setting intercepts to 0
 Define: Standardize
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed items SFAVSUBJ SLESTSUB SENJOYS

 Model: SMotivation BY SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL
 SENJOYING SWASTE SBORING;
 !Removed SFAVSUBJ SLESTSUB SENJOYS;
 !Setting intercepts to 0
 [SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 2a

```
Title: First Order CFA Math ML Estimation Items standardized. Intercepts 0.
No MFAVSUBJ MLESTSUB MENJOYS
Data: File is "C:\AmySharp\Dissertation\HSLS-09
Cleaned_ReverseCode2X_CorrectWghts_16-12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING;
 !Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !Removed items MWASTE MBORING replaced with positive
 !recoded item.
 !Zscore items before setting intercepts to 0
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS

 Model: MIdentity BY MPERSON1 MPERSON2;
 MUtility BY MUSELIFE MUSECLG MUSEJOB;
 MSelfEff BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MInterest BY MENJOYING RMWASTE RMBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 RMWASTE@0 RMBORING@0];
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0

 Output: sampstat stdyx;
```

Model 2b

```
Title: First Order CFA Science ML Estimation Items Standardized Intercepts 0
No SFAVSUBJ SLESTSUB SENJOYS
Data:
File is "C:\AmySharp\Dissertation\HSLS-09
Cleaned_ReverseCode2X_CorrectWghts_16-12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Removed items SWASTE SBORING replaced with postiive
 !recoded item
 !Zscore items before setting intercepts to 0
 Define: Standardize
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING
 !Removed items SFAVSUBJ SLESTSUB SENJOYS;

 Model: SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING RSWASTE RSBORING;
 !Removed SFAVSUBJ SLESTSUB SENJOYS;
 !Setting intercepts to 0
 [SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 RSWASTE@0 RSBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 3a

```
Title: Second Order CFA Math ML Estimation Items standardized Intercepts 0
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-
6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING;
 ! Removed MFAVSUBJ MLESTSUB MENJOYS
 !Zscore items before setting intercepts to 0
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING;
 !Removed MFAVSUBJ MLESTSUB MENJOYS

 Model: !First order factors
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 ! Removed MFAVSUBJ MLESTSUB MENJOYS
 !Second order factor
 MMO by MID MUT MSE MIN;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0];
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0

 Output: sampstat stdyx;
```

Model 3b

```
Title: Second Order CFA Science ML Estimation Items standardized Intercepts 0
No binary items
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-
6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed items SFAVSUBJ SLESTSUB SENJOYS
 !Zscore items before setting intercepts to 0
 Define: Standardize
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed items SFAVSUBJ SLESTSUB SENJOYS

 Model: SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 !Removed items SFAVSUBJ SLESTSUB SENJOYS
 !Second order factor
 SMO BY SID SUT SSE SIN;
 !Setting intercepts to 0
 [SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 4a

```
Title: First Order CFA Math and Science ML Estimation Intercepts 0 No Binary
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_ReverseCode2X_CorrectWghts_16-
12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 !Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !Removed items MWASTE MBORING replaced with positive
 !recoded item.
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Removed items SWASTE SBORING replaced with positive
 !recoded item
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING;

 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING RMWASTE RMBORING;
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING RSWASTE RSBORING;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 RMWASTE@0 RMBORING@0
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 RSWASTE@0 RSBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 4b

```
Title: First Order CFA Math and Science ML Estimation Intercepts 0 No Binary
Correlations Restricted
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS

 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 ! Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Constraining Correlations only like math and science factors correlate
 MID with SUT@0 SSE@0 SIN@0;
 MUT with SID@0 SSE@0 SIN@0;
 MSE with SID@0 SUT@0 SIN@0;
 MIN with SID@0 SUT@0 SSE@0;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 4c

```
Title: Second Order CFA Math and Science ML Estimation Intercepts 0 No Binary
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS

 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 ! Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Second order factor math
 MMO by MID MUT MSE MIN;
 !Second order factor science
 SMO BY SID SUT SSE SIN;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Model 4d

```
Title: Second Order CFA Math and Science ML Estimation Intercepts 0 No Binary Like 1Fs
are 2nd Order Fs
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS

 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 ! Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 ! Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Second order factors from like first order factors
 ID by MID SID;
 UT by MUT SUT;
 SE by MSE SSE;
 IN by MIN SIN;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0
 !Removed MFAVSUBJ@0 MLESTSUB@0 MENJOYS@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Removed items SFAVSUBJ@0 SLESTSUB@0 SENJOYS@0

 Output: sampstat stdyx;
```

Outcome Model: STEM Credits, MLE with No Weights

```
Title: STEM Credits ML Estimation Intercepts 0 No Binary All Fs Pred Factor Var 1
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_ReverseCode2X_CorrectWghts_16-12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 !Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !Removed items MWASTE MBORING replaced with positive
 !recoded item.
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Removed items SWASTE SBORING replaced with positive
 !recoded item
 X3CRDSTM;
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !choosing not to standardize x1mtscore because already a standardized measure.

 Model: !First order factors math
 MID BY MPERSON1* MPERSON2;
 MID@1;
 MUT BY MUSELIFE* MUSECLG MUSEJOB;
 MUT@1;
 MSE BY MTESTS* MTEXTBOOK MSKILLS MASSEXCL;
 MSE@1;
 MIN BY MENJOYING* RMWASTE RMBORING;
 MIN@1;
 !First order factors science
 SID BY SPERSON1* SPERSON2;
 SID@1;
 SUT BY SUSELIFE* SUSECLG SUSEJOB;
 SUT@1;
 SSE BY STESTS* STEXTBOOK SSKILLS SASSEXCL;
 SSE@1;
 SIN BY SENJOYING* RSWASTE RSBORING;
 SIN@1;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 RMWASTE@0 RMBORING@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 RSWASTE@0 RSBORING@0];
 !Outcome
 X3CRDSTM on MID MUT MSE MIN SID SUT SSE SIN

 Output: sampstat stdyx;
```

Outcome Model: STEM GPA, MLE with No Weights

```
Title: STEM GPA ML Estimation Intercepts 0 No Binary All Fs Predicting GPA Factor Var 1
Data:
File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_ReverseCode2X_CorrectWghts_16-12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 !Removed Items MFAVSUBJ MLESTSUB MENJOYS
 !Removed items MWASTE MBORING replaced with positive
 !recoded item.
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !Removed items SWASTE SBORING replaced with positive
 !recoded item
 X3GPASTM;
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING
 !Removed MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING;
 !Removed Items SFAVSUBJ SLESTSUB SENJOYS
 !choosing not to standardize x1mtscore as already standardized

 Model: !First order factors math
 MID BY MPERSON1* MPERSON2;
 MID@1;
 MUT BY MUSELIFE* MUSECLG MUSEJOB;
 MUT@1;
 MSE BY MTESTS* MTEXTBOOK MSKILLS MASSEXCL;
 MSE@1;
 MIN BY MENJOYING* RMWASTE RMBORING;
 MIN@1;
 !First order factors science
 SID BY SPERSON1* SPERSON2;
 SID@1;
 SUT BY SUSELIFE* SUSECLG SUSEJOB;
 SUT@1;
 SSE BY STESTS* STEXTBOOK SSKILLS SASSEXCL;
 SSE@1;
 SIN BY SENJOYING* RSWASTE RSBORING;
 SIN@1;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 RMWASTE@0 RMBORING@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 RSWASTE@0 RSBORING@0];
 !Outcome
 X3GPASTM on MID MUT MSE MIN SID SUT SSE SIN;

 Output: sampstat stdyx;
```

Outcome Model: STEM Career Status, WLSMV with No Weights

```
Title: SEM STEM Career Theta All Fs Predicts Factor Var 1
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_ReverseCode2X_CorrectWghts_16-
12-15.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS RMWASTE RMBORING RSWASTE RSBORING (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING SFAVSUBJ SLESTSUB SENJOYS
 RX230OCC;
 Categorical = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 RMWASTE RMBORING MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 RSWASTE RSBORING SFAVSUBJ SLESTSUB SENJOYS RX230OCC;

 Analysis: Parameterization = Theta;
 Model: !First order factors math
 MID BY MPERSON1* MPERSON2;
 MID@1;
 MUT BY MUSELIFE* MUSECLG MUSEJOB;
 MUT@1;
 MSE BY MTESTS* MTEXTBOOK MSKILLS MASSEXCL;
 MSE@1;
 MIN BY MENJOYING* RMWASTE RMBORING MFAVSUBJ
 MLESTSUB MENJOYS;
 MIN@1;
 !First order factors science
 SID BY SPERSON1* SPERSON2;
 SID@1;
 SUT BY SUSELIFE* SUSECLG SUSEJOB;
 SUT@1;
 SSE BY STESTS* STEXTBOOK SSKILLS SASSEXCL;
 SSE@1;
 SIN BY SENJOYING* RSWASTE RSBORING SFAVSUBJ
 SLESTSUB SENJOYS;
 SIN@1;
 !Outcome Predicted
 RX230OCC ON MID MUT MSE MIN SID SUT SSE SIN;

 Output: sampstat stdyx;
```

Invariance Test of Outcome Model: STEM Credits, MLE with No Weights

Constrained Model:

```
Title: STEM Credits ML Estimation Intercepts 0 No Binary All F's Predict Invariance Constrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = X1SEX MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING!Removed Items SFAVSUBJ SLESTSUB SENJOYS
 X3CRDSTM;
 Grouping = X1SEX (1 = Male 2 = Female);
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Outcome
 X3CRDSTM on MID MUT MSE MIN SID SUT SSE SIN
 Output: sampstat stdyx;
```

Unconstrained Model

```
Title: STEM Credits ML Estimation Intercepts 0 No Binary All F's Predict Invariance Unconstrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = STU_ID X1SEX X1TXMTH X1TXMTSCOR
 !SCALE VARIABLES
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING MFAVSUBJ
 SFAVSUBJ FAVSUBJ MLESTSUB SLESTSUB LEASTSUBJ
 MENJOYS SPERSON1 SPERSON2 SUSELIFE
 SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL
 SENJOYING SWASTE SBORING
 SENJOYS
 !OUTCOME VARIABLES
 X230OCC RX230OCC X3GPASTM X3CRDSTM  !Weight variables removed to save space
```

Invariance Test of Outcome Model: STEM GPA, MLE with No Weights

Constrained Model:

```
Title: STEM GPA ML Estimation Intercepts 0 No Binary All Fs Predicting GPA Inv Test Constrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X2300CC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX2300CC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = X1SEX MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING
 X3GPASTM;
 Grouping = X1SEX (1 = Male 2 = Female);
 Define: Standardize
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING;
 Model: !First order factors math
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING;
 !First order factors science
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING;
 !Setting intercepts to 0
 [MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
 MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
 MWASTE@0 MBORING@0
 SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
 STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
 SWASTE@0 SBORING@0];
 !Outcome
 X3GPASTM on MID MUT MSE MIN SID SUT SSE SIN;
 Output: sampstat stdyx;
```

Unconstrained Model

```
Title: STEM GPA ML Estimation Intercepts 0 No Binary All F's Predict Invariance Unconstrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X2300CC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX2300CC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = X1SEX MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
```

```
MWASTE MBORING
SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
SWASTE SBORING!Removed Items SFAVSUBJ SLESTSUB SENJOYS
X3GPASTM;
Grouping = X1SEX (1 = Male 2 = Female);
Define: Standardize
MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
MWASTE MBORING SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
SWASTE SBORING;
Model:
!First order factors math
MID BY MPERSON1(L1)
MPERSON2(L2);
MUT BY MUSELIFE(L3)
MUSECLG(L4)
MUSEJOB(L5);
MSE BY MTESTS(L6)
MTEXTBOOK(L7)
MSKILLS(l8)
MASSEXCL(L9);
MIN BY MENJOYING(L10)
MWASTE(L11)
MBORING(L12);
!First order factors science
SID BY SPERSON1(L13)
SPERSON2(L14);
SUT BY SUSELIFE(L15)
SUSECLG(L16)
SUSEJOB(L17);
SSE BY STESTS(L18)
STEXTBOOK(L19)
SSKILLS(L20)
SASSEXCL(L21);
SIN BY SENJOYING(L22)
SWASTE(L23)
SBORING(L24);
!Need to fix the first order factor intercepts to zero for the model to be identified
[MID@0 MUT@0 MSE@0 MIN@0 SID@0 SUT@0 SSE@0 SIN@0
!Setting intercepts to 0
MPERSON1@0 MPERSON2@0 MUSELIFE@0 MUSECLG@0 MUSEJOB@0
MTESTS@0 MTEXTBOOK@0 MSKILLS@0 MASSEXCL@0 MENJOYING@0
MWASTE@0 MBORING@0
SPERSON1@0 SPERSON2@0 SUSELIFE@0 SUSECLG@0 SUSEJOB@0
STESTS@0 STEXTBOOK@0 SSKILLS@0 SASSEXCL@0 SENJOYING@0
SWASTE@0 SBORING@0];
!Outcome
X3GPASTM on MID(L25)
MUT(L26)
MSE(L27)
MIN(L28)
SID(L29)
SUT(L30)
SSE(L31)
SIN(L32)
Model Female:
!First order factors math
MID BY MPERSON1@1 MPERSON2;
MUT BY MUSELIFE@1 MUSECLG MUSEJOB;
MSE BY MTESTS@1 MTEXTBOOK MSKILLS MASSEXCL
MIN BY MENJOYING@1 MWASTE MBORING;
!First order factors science
SID BY SPERSON1@1 SPERSON2;
SUT BY SUSELIFE@1 SUSECLG SUSEJOB;
SSE BY STESTS@1 STEXTBOOK SSKILLS SASSEXCL;
SIN BY SENJOYING@1 SWASTE SBORING;
!Outcome
X3GPASTM on MID MUT MSE MIN SID SUT SSE SIN
Output: sampstat stdyx
```

Invariance Test of Outcome Model: STEM Career Status, WLSMV with No Weights

Constrained Model

```
Title: SEM STEM Career Theta All Fs Predicts Inv Test Constrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 usevar = X1SEX MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS
 RX230OCC;
 Categorical = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
 STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
 SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS RX230OCC;
 Grouping = X1SEX (1 = Male 2 = Female);
 Analysis: Parameterization = Theta;
 DIFFTEST=STEM Career DiffTest.dat;
 Model:
 !First order factors
 !Constrained to be equal
 MID BY MPERSON1 MPERSON2;
 MUT BY MUSELIFE MUSECLG MUSEJOB;
 MSE BY MTESTS MTEXTBOOK MSKILLS MASSEXCL;
 MIN BY MENJOYING MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS;
 SID BY SPERSON1 SPERSON2;
 SUT BY SUSELIFE SUSECLG SUSEJOB;
 SSE BY STESTS STEXTBOOK SSKILLS SASSEXCL;
 SIN BY SENJOYING SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS;
 !Outcome Predicted
 RX230OCC ON MID MUT MSE MIN SID SUT SSE SIN;
 Output: sampstat stdyx;
```

Unconstrained Model

```
Title: SEM STEM Career Theta All Fs Predicts Inv Test Unconstrained
Data: File is "C:\AmySharp\Dissertation\HSLS-09 Cleaned_All Reverse Code_16-6-30.csv";
Variable: Names = [removed to save space]
 Missing are STU_ID X1SEX (-7, -8, -9)
 X230OCC X1TXMTH X1TXMTSCOR (-6, -7, -8, -9)
 MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING MWASTE
 MBORING MFAVSUBJ SFAVSUBJ FAVSUBJ MLESTSUB
 SLESTSUB LEASTSUBJ MENJOYS SPERSON1
 SPERSON2 SUSELIFE SUSECLG SUSEJOB STESTS
 STEXTBOOK SSKILLS SASSEXCL SENJOYING SWASTE
 SBORING SENJOYS (-7, -8, -9)
 RX230OCC (-6, -7, -8, -9, 9)
 X3GPASTM X3CRDSTM (-1, -6, -7, -8, -9);
 Usevar = X1SEX MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
 MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
 MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS
 SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
```

```
STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS
RX230OCC;
Categorical = MPERSON1 MPERSON2 MUSELIFE MUSECLG MUSEJOB
MTESTS MTEXTBOOK MSKILLS MASSEXCL MENJOYING
MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS
SPERSON1 SPERSON2 SUSELIFE SUSECLG SUSEJOB
STESTS STEXTBOOK SSKILLS SASSEXCL SENJOYING
SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS RX230OCC;
Grouping = X1SEX (1 = Male 2 = Female);
Analysis: Parameterization = Theta;
Model:
!First order factors
!Constrained to be equal
MID BY MPERSON1 (L1) MPERSON2 (L2);
MUT BY MUSELIFE (L3) MUSECLG (L4) MUSEJOB (L5);
MSE BY MTESTS (L6) MTEXTBOOK (L7) MSKILLS (L8) MASSEXCL (L9);
MIN BY MENJOYING (L10) MWASTE (L11) MBORING (L12) MFAVSUBJ (L13)
MLESTSUB (L14) MENJOYS (L15);
SID BY SPERSON1 (L16) SPERSON2 (L17);
SUT BY SUSELIFE (L18) SUSECLG (L19) SUSEJOB (L20);
SSE BY STESTS (L21) STEXTBOOK (L22) SSKILLS (L23) SASSEXCL (L24);
SIN BY SENJOYING (L25) SWASTE (L26) SBORING (L27) SFAVSUBJ (L28)
SLESTSUB (L29) SENJOYS (L30);
!Outcome Predicted
RX230OCC ON MID (L31) MUT (L32) MSE (L33) MIN (L34) SID (L35)
SUT (L36) SSE (L37) SIN (L38);
Model Female:
!Removing labels frees up factor loadings. Free to differ.
!Need to set reference indicator to 1.
MID BY MPERSON1@1 MPERSON2;
MUT BY MUSELIFE@1 MUSECLG MUSEJOB;
MSE BY MTESTS@1 MTEXTBOOK MSKILLS MASSEXCL;
MIN BY MENJOYING@1 MWASTE MBORING MFAVSUBJ MLESTSUB MENJOYS;
SID BY SPERSON1@1 SPERSON2;
SUT BY SUSELIFE@1 SUSECLG SUSEJOB;
SSE BY STESTS@1 STEXTBOOK SSKILLS SASSEXCL;
SIN BY SENJOYING@1 SWASTE SBORING SFAVSUBJ SLESTSUB SENJOYS;
!Outcome Predicted
RX230OCC ON MID MUT MSE MIN SID SUT SSE SIN;
Output: sampstat stdyx;
Savedata: DIFFTEST=STEM Career DiffTest.dat;
```