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A Structural and Intersectional Analysis of High School Students' STEM Career Development Using a Social Cognitive Career Theory Framework

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Abstract

This research examined high school students' STEM career development using a Social Cognitive Career Theory framework. Data used in this study were from High School Longitudinal Study of 2009. Intersectional approaches were employed to gain an in-depth understanding of student characteristics, as well as identify potential differences in students' STEM behaviors. Further, examinations of the STEM career development process were conducted using structural equation modeling statistical techniques. Findings suggest that prior learning experiences (i.e., math aptitude, informal STEM learning experiences, and math and science identity) and environmental supports and barriers (e.g., informal STEM exposure) are significant influences on students' STEM career development. Additionally, when considering the entire student population, students' math and science self-efficacy, outcome expectation, and interest are significant predictors of STEM career intentions and STEM major selection. However, multi-group structural equation modeling analyses, particularly with regard to race/ethnicity and socio-economic status, indicate substantial between group differences in students' STEM career development. When examining race, the proposed model was most predictive for White students and least predictive for Black students. STEM career intention was significantly influenced by math interest and math outcome expectation for White and Asian students, but these factors were not predictive for Latino and Black students. Additionally, self-efficacy was predictive of STEM major selection for all racial/ethnic groups, except Black students. Finally, outcome expectation was shown to significantly influence STEM major selection for White students, but not for any of the other racial/ethnic groups. Similar trends emerged when analyzing the proposed model by students' socio-economic status—the model was most predictive of STEM career development for students in the highest socio-economic quintiles, and least predictive for those in the lowest.

A STRUCTURAL AND INTERSECTIONAL ANALYSIS OF HIGH SCHOOL STUDENTS' STEM CAREER DEVELOPMENT USING A SOCIAL COGNITIVE CAREER THEORY FRAMEWORK

by

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Chapter 1: Introduction

Background of Study

Increasingly, Science, Technology, Engineering, and Mathematics (STEM) is becoming a topic dominating discussion among diverse stakeholders, including educators, policy makers, government officials, industry stakeholders, and funding entities (Breiner, Johnson, Harkness, & Koehler, 2012). Its implication has effects that extend across issues of national competiveness, global leadership, education policy, economic growth, social mobility, and innovation (Committee on STEM Education, 2013; National Science Board, 2015; U.S. Department of Education, 2016; Xie, Fang, & Shauman, 2015). The wide spread prominence assigned to STEM has resulted in the formation of organizations, development of strategies, and implementation of initiatives across the nation, all of which target some aspect of STEM advancement. The 2016 President's Budget gave priority to STEM education, with $3 billion being requested to go toward STEM efforts, a 3.8 percent increase in STEM education investments from 2015 (National Economic Council and Office of Science and Technology Policy, 2015). The Committee on STEM Education (CoSTEM), an organization comprised of 12 mission-science agencies and the Department of Education, has begun strategizing approaches to improve K-12 STEM instruction, increase youth STEM engagement, improve undergraduate STEM experience, better serve populations historically underrepresented in STEM, and design graduate education that better aligns with the STEM workforce (CoSTEM, 2013). The STEM Education Coalition, an alliance of advocates of STEM education, has produced comprehensive recommendations on STEM Education. Key elements that they have identified as essential to a national STEM education agenda include: bipartisanship among stakeholders; an all-hands-on-deck approach; broadening of the pipeline; high quality educator preparation; embracement of innovation; workforce focus; and federal funding of STEM-related educational programs, research, and innovation (STEM Education Coalition, 2016). The recently legislated Every Child Succeeds Act includes provisions on STEM standards and assessments, professional development efforts for STEM educators, and grants funds for student enrichment activities relating to STEM (Every Student Succeeds Act, 2015). Each of these is an example of recent actions taken to strengthen our nation's STEM front.

Though STEM initiatives continue to lead national efforts, a lack of consensus regarding what STEM means has impeded progress (Bybee, 2010). Inconsistencies in how STEM is defined, misalignment between stages of the STEM pipeline, and non-uniformity in the identification of careers inclusive to the STEM workforce are detrimental to efforts made to enhance STEM education and strengthen the STEM workforce (Gerlach, 2012). Further, variations in the operationalization of psychological constructs, like STEM- identity, interest, self-efficacy, and goal expectation, convolute their meanings and distort their relationships (Lent et al., 2002). Moreover, nuances like the disproportionate underrepresentation of diverse populations along STEM pathways (Landivar, 2013) and a lack of consideration of the influence of environmental contexts on STEM participation (Wang, 2012) hinder progress toward building a robust national STEM workforce. Investigating the manner with which these forces might interact, however, may provide the insight needed to understand the complexity of the STEM career development process. This critical examination allows for a systems-level investigation into how these inter-locking mechanisms may shape individuals' STEM-related behaviors.

Statement of the Problem

The United States must continue to meet global competitive needs to maintain leadership in today's scientific and technological era. The Obama Administration named science and innovation as key components in building a strong economic infrastructure (National Economic Council & Office of Science and Technology Policy, 2015). It is projected that occupations in Science, Technology, Engineering, and Mathematics (STEM) fields will grow at a rate of 1.7 times faster than non-STEM professions (Office of Science and Technology Policy, 2012). While a robust progression of our nation's STEM industry is desired to support advancement, it has been met with unanticipated challenges. The growth in STEM calls for 1 million more professionals than are projected to graduate in the next decade to meet the demands of this emergent STEM workforce (President's Council of Advisors on Science and Technology, 2012). It is urgent that efforts are engaged immediately to fill this substantial need. Otherwise, our nation's STEM infrastructure is at risk, which directly threatens America's ability to maintain global competitiveness. While this shortage in workforce capacity is a critical issue plaguing our nation, the depth of this labor market deficiency sheds necessary light onto the inequities present within current STEM workforce trends.

The underrepresentation of minority populations within STEM remains an endemic (Fealing, Lai, & Myers, 2015). There are two major issues associated with this phenomenon. The first issue is directly related to concerns about the projected shortage of qualified STEM professionals; a lack of inclusion of these underrepresented groups within STEM further impedes efforts at building a robust workforce (PCAST, 2012). Latinos are the fastest growing demographic group in America, representing 17.6 percent of the population (US Census Bureau, 2015) and making up more than 16 percent of the labor market, but only account for 7 percent of the STEM workforce (Bureau of Labor Statistics, 2015). Similarly, African Americans make up 13.3 percent of the U.S. population (US Census Bureau, 2015), comprise 12 percent of the national labor market (Bureau of Labor Statistics, 2015), yet only account for 6 percent of the STEM workforce (Landivar, 2013). These same discrepancies hold true when analyzing workforce characteristics of other racial/ethic minorities, excluding Asian Americans, as well as individuals of low socio-economic status.

The second issue, and perhaps most important, emphasizes the systematic inequity that has allowed for these patterns to emerge. The disproportionate absence of marginalized communities within STEM is crippling. Historically, barriers to success through systems of perpetual inequality, particularly those relating to educational disparities, unequal employment structures, and thus, racial and gendered wealth gaps, (Darling-Hammond, 1998; Shapiro, Mechede, & Osoro, 2013), overwhelmingly replaced opportunities for social and economic upward mobility (Carter, 2006). Though the STEM workforce has been identified as crucial for economic growth on both an individual and national level, diversity within STEM has remained stagnant over the last 15 years (Change the Equation, 2015), depriving underrepresented minorities of the opportunity to reap the benefits associated with participation in this rigorous labor market. College graduates with degrees in STEM fields are positioned to attain higher occupational earnings and professional social status (Russell & Atwater, 2005). Thus, the disproportionate participation of those underrepresented in STEM adversely affects their long-term well-being, hence perpetuating socioeconomic inequality.

While strides are being made to increase our STEM workforce, it is imperative that we intentionally and effectively target our efforts toward historically underrepresented students' interest, participation, and persistence within STEM, too. Educators, policy-makers, and researchers are increasingly concerned with STEM advancement. However, now more than ever, as we are building toward that landscape of innovation, we must ensure that equity is equally emphasized. Only then will we truly epitomize a nation of promise.

Purpose of Study

In recognition of the immediate need for STEM professionals, this research was motivated by the urgency to increase participation along STEM pathways more generally, while also directing attention to those who have remained underrepresented. In order to facilitate a growth in STEM membership and foster an increase in STEM workforce capacity, one must understand—fundamentally— how individuals come to make the choice to engage in particular career-related behaviors, and ultimately decide to pursue a specific profession. High school is a critical period in one's life in terms of making decisions to pursue educational opportunities related to career interests. While students typically begin to formulate attitudes toward particular academic and career domains during the middle school years (Fouad & Smith, 1996; Turner & Lapan, 2005), high school is when these dispositions are solidified, as heightened career maturity is achieved (Powell & Anthony, 1998). Thus, this study will focus on high school students' career development process as it relates to STEM. In trying to conceptualize what this process might look like, it is essential to conduct an examination of how the complex interaction among diverse factor-types (e.g., cognitive, environmental, psychological) shapes an individual's career-oriented progression. In addition to fundamentally and intricately investigating the STEM career development process, investigations of career development must be *critically* engaged. Not considering the cultural, economic, and social implications of STEM career development would perpetuate normative rhetoric and promote traditional systems that continue to dictate who gets to participate within STEM (and by extension, who remains absent). The purpose of this research is to critically examine high school students' STEM career development process in light of each of these elements. Essentially, this investigation will aid in the facilitation of STEM participation and in an expansion of the STEM pipeline.

Most research aimed at broadening STEM participation centers around persistence and attainment among students already in STEM (Andersen & Ward, 2014; Guo et al., 2015; Russell & Atwater, 2005). There is an insufficient amount of attention placed on factors relating to interest in and entrance into STEM, which are arguably most critical in terms of initially attracting individuals into the pipeline (Wang, 2013). Further, previous research has focused on isolated factors that may contribute to high school students' academic and career trajectory in STEM, failing to consider the complex interplay among cognitive, psychological, and environmental variables influencing the career development process (Guo et al, 2015). The career development process is a dynamic, long-term progression that is shaped by a series of activities and life experiences. As such, the decision to pursue a STEM career is a longitudinal process that builds across intervals of time. Thus, this complex phenomenon is best understood when taking a more holistic perspective that extends across both the secondary and post-secondary stages of education. Finally, the composition of factors influencing career development may vary based on personal characteristics. Consequently, while analyses of the STEM career development process of high school students as a whole must be investigated, it is imperative that it is also examined by subpopulation to identify potential differences.

Theoretical Framework

Social Cognitive Career Theory

This study is guided by assumptions outlined in Social Cognitive Career Theory (SCCT) (Lent et al., 1994). SCCT holds that there exists a complex interplay among goals, self-efficacy, and outcome expectations, which results in the self-regulation of behavior (Lent et al, 2002). These building blocks of career development are the devices by which people exercise personal agency, and afford individuals with the opportunity to formulate academic- and career-oriented interests, choices, and performances. While people may be active agents in the construction of their own career-related outcomes, the career development process extends beyond a person's cognitive state of being. Social Cognitive Career Theory posits that there are "mutual, interacting influences among persons, their environment, and behavior" that "operate as interlocking mechanisms that affect one another bidirectionally." (Lent et al, 2002, p. 261). A multitude of factors act simultaneously with a person's cognition, affecting the range and nature of their career possibilities (Lent et al, 2002).

Social Cognitive Career Theory presents career-related interest, choice, and performance through three interrelated models (Lent et al., 2002). Though these models are interconnected, they can each stand on their own as a distinct framework, i.e., Interest Model, Choice Model, and Performance Model (Lent et al., 2002). Central to the conceptualization of the career development process within the context of this study is the Choice Conceptual Framework that builds upon and thus inherently includes the Interest Model. The Performance Model will not be included in this study, as it goes beyond the scope of this work. This research examines how students' interest in STEM relates to their intent to pursue a STEM career, and their subsequent selection of a STEM major in college. These milestones align with the interests, choice goals, and choice actions components of SCCT's Choice Model. Naturally, college performance and attainments would be the next milestone in the STEM career trajectory. While STEM-related performances and attainments during college are important, these phenomena include their own set of complexities that are outside the boundaries of this study.

The Interest Model, which serves as the foundation of the interlocking models, asserts that an individual's self-efficacy and outcome expectation regarding task involvement has a direct affect on the subsequent cultivation of their interests (Lent et al., 2002). Furthermore, developing interests promote goal formation for activity involvement (Lent et al., 2002). These goals then translate to increased likelihood of activity engagement. Finally, attainments gained from activity engagement form a feedback loop, which either maintains or modifies self-efficacy and outcome expectation, thus interest, and so forth (Lent et al., 2002).

Going further, SCCT's Choice Model emphasizes those person, contextual and learning influences on choice behaviors (Lent et al., 2002). Moreover, goals and actions that were referred to in general terms within the Interest Model now characterize career-related goals and the actions required to implement them in the Choice Model. Integrated, SCCT's Interest and Choice Models offer a conceptual framework for understanding the "developmental continuity between the evolution of basic vocational interests and their eventual translation into career-relevant choices" (Lent et al, 2002, p. 272). Social Cognitive Career Theory's Choice Model is depicted below. See fig. 1.

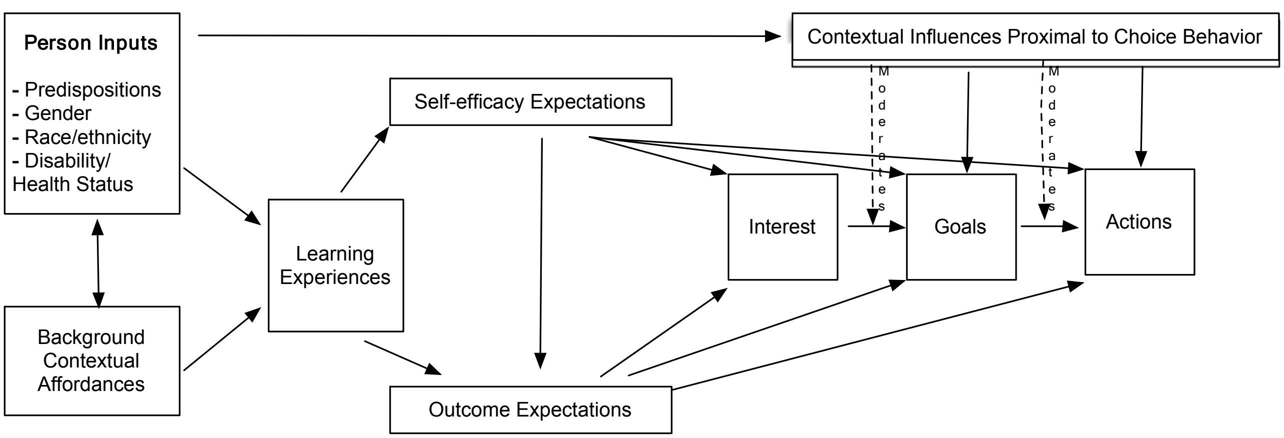


Figure 1. *Model of social cognitive influences on career choice behaviors*
(Lent, Brown, & Hackett, 1994*).*

Though Social Cognitive Career Theory acknowledges that environmental and other contextual factors influence the career development process, most research employing a SCCT framework focus on person-cognitive variables in isolation from essential environmental variables that contribute to various facets of an individual's career-choice behaviors (Lent, Brown & Hackett, 2000). When trying to understand career development processes of high school students belonging to diverse populations and backgrounds, the influence of the environment needs to be considered and the cultural context in which occupational choice takes place must be highlighted. This becomes especially significant when trying to help particular racial, cultural, and gendered groups that have remained underrepresented in particular career domains - like STEM - increase their levels of participation within those respective fields.

STEM Career Development Conceptual Model

Using the Choice Model as a theoretical framework supports this study's aim to go beyond understanding how individuals cultivate STEM interest by also examining the process by which students engage in STEM career-related behaviors. Modifications were made to the Choice Model to further examine high school students' experiences and more closely reflect conditions of high school contexts. Based on underlying assumptions outlined within Social Cognitive Career Theory, and the Choice Model particularly, the following conceptual model was developed. See Fig. 2.

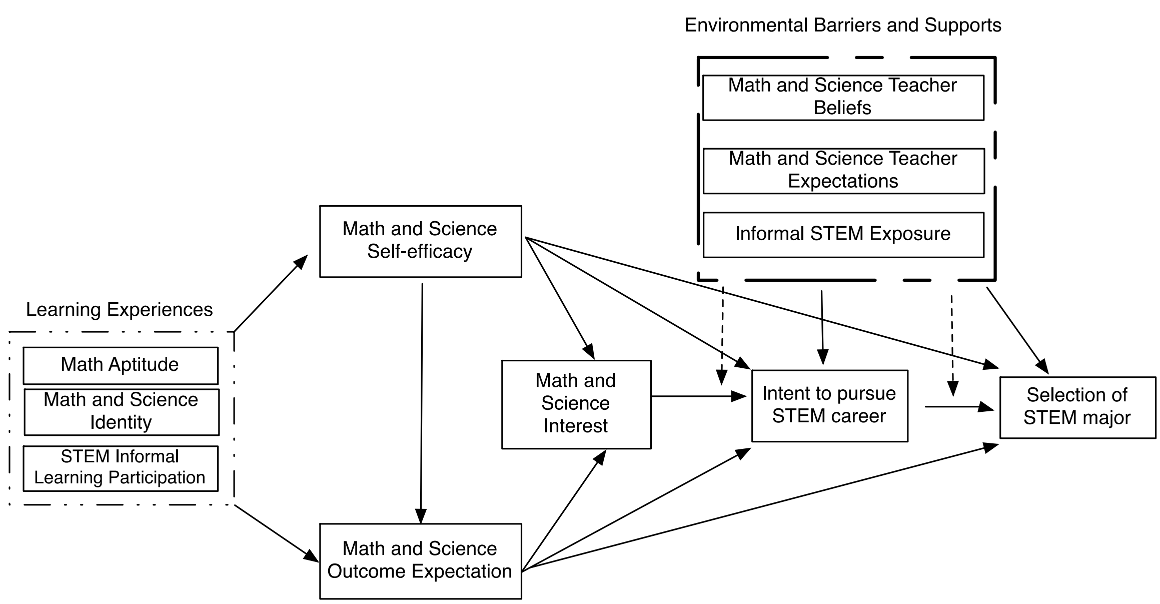


Figure 2. *Conceptual Model of the STEM Career Development Process*

Within this model, constructs relating to self-efficacy, outcome expectation, interest development, and goal formation act in similar ways described in the general Choice Model. It is important, however, to highlight the role of learning experiences and environmental influences in this framework. Past STEM-oriented learning experiences relating to math performance, identity cultivation, and participation within informal STEM learning were found to shape a person's interests, values, and choices (Lent at al., 2002). Further, environmental influences within the school setting, like teacher beliefs, teacher expectations, and school facilitated exposure to STEM-related mentors, programs, or other experiences are opportunity structure factors that directly and indirectly affect career behavior (Nugent et al., 2015).

Critical Paradigm

A critical investigative approach was engaged through an intersectional lens. Intersectionality (Crenshaw, 1989) recognizes the overlap and intersection among social identities and examines how these socially constructed characterizations exist within systems that often perpetuate oppression, domination, or discrimination. Intersectional approaches take into account the complexities, with regard to both subjects and structures, that shape the multiple dimensions of people's lived experiences (Crenshaw, 1991). This theoretical methodology was used to examine the manners with which intersecting social categories (i.e., race, gender, and class) are situated within the context of larger socio-political systems (i.e. school environments) and how the intersecting interactions might then shape youth STEM career development.

Research Questions

The intent of this research was to understand high school students' developmental progression relating to their decisions to participate in STEM-related activities, cultivate STEM careers intentions, and ultimately, select a STEM major in college. By employing a conceptual model guided by Social Cognitive Career Theory (Lent et al., 2002), this study examined the effects of cognitive, psychological, and environmental influences on STEM career pursuits. Additionally, since math provides a foundation for STEM and is often used an indicator of STEM participation (Sax et al., 2015; Wang, 2013), a math-specific model based on the core SCCT framework was utilized to examine potential group differences in students' STEM career development. This research addressed the following questions:

Research Question 1 (RQ1): Are there differences in STEM career intentions or STEM major selections, based on race/ethnicity, gender, or socio-economic status?

Research Question 2 (RQ2): What is the relationship among cognitive, psychological, and environmental factors as related to high school students' intent to pursue a STEM career and selection of a STEM major?

Research Question 3 (RQ3): Are there differences in how math-related core Social Cognitive Career Theory predictors (i.e., math- self-efficacy, outcome expectation, and interest) influence STEM career intentions and major selection, based on gender, race/ethnicity, or socio-economic status?

Data

These research questions were examined through the proposed conceptual model using the National Center for Education Statistics' High School Longitudinal Study of 2009 (HSLS:09) dataset. HSLS:09 is a nationally representative, longitudinal study of more than 23,000 high school students from 944 schools in 2009 (Ingles et al., 2011). There have been three waves of data collection since the start of the study (i.e., 2009, 2011, and 2013), with the fourth wave currently in collection. Additionally, HSLS:09 includes measures of constructs key to this research, including those relating to students' math- and science- self-efficacy, outcome expectation, interests, informal learning participation, and identity, as well as math aptitude (Ingles et al., 2011). It also includes school- and teacher-level measures that provide the environmental context desired for this study (Ingles et al., 2011). HSLS:09 focused on student academic and career trajectories, with particular attention to STEM-related pursuits (Ingles et al., 2011).

To date, there have been very few studies conducted using these data, none of which examined issues core to this research. Prior studies have investigated disparities in students' post-secondary educational plans, with emphasis on computer science (Bean et al., 2016) and STEM persistence of high-ability students (Andersen & Ward, 2014). This research, however, focused on STEM career development. Further, this study leveraged the longitudinal nature of HSLS:09, rather than focusing solely on particular cross-sectional waves as engaged in the two previous studies.

Summary

This research examined the career development process of high school students as a means of understanding the complex interaction among factors contributing to their decision to pursue STEM. Longitudinal data were used to investigate effects of cognitive, psychological, and environmental variables on STEM career development, and how this phenomenon looked different when considering diverse socio-demographic characteristics and backgrounds. By developing a better understanding of how students cultivate vocational interests and subsequently construct career-oriented behaviors, better interventions and support structures can be designed to aid in nurturing STEM prospects. The following chapter will discuss literature related to STEM composition, career development, and critical analysis, all of which provide a greater context of understanding for this study. Key terms used throughout this study are defined below.

Definition of Terms

STEM Pipeline: Pathways through STEM, which begins in primary school, and then continues through postsecondary education and beyond. Critical junctures of the pipeline trajectory include entrance into college with a STEM major, completion of a degree in a STEM field, and participation in the STEM workforce.

*Career Development Process***:** the developmental progression of interest formation, career selection, and performance (Lent et al, 2002).

Self-Efficacy: A person's belief about their capability "to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 391). Self-efficacy beliefs are dynamic, contextualized dispositions that interact with other person, behavior, and environmental factors in complex ways (Lent et al., 2002). Further, self-efficacy is developed and adapted via four types of learning experiences: personal performance accomplishments, vicarious learning, social persuasion, and physiological and affective states (Bandura, 1997).

Outcome Expectation: A person's belief about the consequence or outcome of performing particular behaviors (Lent et al., 2002, p 263). These beliefs are cultivated through learning experiences, and may be shaped by self-efficacy when outcomes are determined by the quality of one's performance (Lent et al., 2002). Outcome expectations are attributed as playing a major role in motivating behavior.

Interest: A person's pattern of likes, dislikes, and indifferences regarding various discipline, occupation, and career-relevant activities; key determinant of career choice (Lent et al., 2002).

Goals: Determination to engage in a particular activity or to effect a particular future outcome (Bandura, 1986). Thus, goals represent "a critical mechanism through which people exercise personal agency or self-empowerment," as goal-setting helps individuals "organize, guide, and sustain one's own behaviors, even through long intervals, and without external reinforcement" (Lent et al., 2002, p. 263).

Chapter 2: Literature Review

This research examined the career development process of high school students as a means of understanding the complex interaction among factors contributing to their decision to pursue STEM. Chapter 2 begins by reviewing how STEM in conceptualized within diverse paradigms. Similarities and differences are noted regarding definitions assigned to STEM based on context, taxonomies of STEM composition based on institution, and how areas of difference and overlap can vary depending on stakeholder perception. Next, STEM higher education trends are discussed. During the examination of post-secondary STEM contexts, demographic information describing individuals who participate within STEM, rates of STEM attrition, and strategies being implemented for increased STEM retention are presented. Examination of the composition of the STEM workforce will follow, where parallels between postsecondary contexts and the workforce are made apparent. Detailed demographic information of the workforce is provided, with disaggregation by STEM discipline, race, and gender.

After literature on STEM is presented from these diverse perspectives, the theoretical frameworks guiding this research are further described. Detailed descriptions of Social Cognitive Career Theory are provided, including information regarding its background and roots, major assumptions, key concepts, and applicability to STEM career development. Finally, frameworks that allow for a critical examination of findings are identified. These include Social Cognitive Career Theory and Intersectionality. Approaches for critical analysis are discussed for each.

Defining STEM

Coined by Dr. Ramaley of the National Science Foundation in 2001, STEM was meant to represent the meaningful connection that exists among Science, Technology, Engineering, and Mathematics (Patton, 2013). Previously, the term SMET was used, but Dr. Ramaley felt this term subtly implied that science and mathematics came first or were of greater significance than technology and engineering. STEM, on the other hand, suggests that these subjects share an integrated relationship. Dr. Ramaley held that STEM made more sense conceptually and aesthetically, as "science and math carry as the core their applications of technology and engineering" (as cited in Patton, 2013, para. 5). Furthermore, STEM was much more appealing in its sound.

Fundamentally speaking, STEM is simply an acronym for Science, Technology, Engineering, and Mathematics. Conceptually, however, its definition is widely unknown (Gerlach, 2012; NSB, 2015). This holds true for its application across various contexts, but especially with respect to education and the workforce. While STEM is most often spoken about with regard to education and the workforce, part of the confusion that exist when trying to define this construct stems from rarely discussing these two categories of STEM in conjunction (Gerlach, 2012).

<u>STEM Education</u>

Diverse perceptions of STEM have led to challenges with regard to its implementation within educational settings (Marrero, Gunning & Germain-Williams, 2014). There is a general understanding of characteristics that are inclusive of STEM (e.g., interdisciplinary; real-world applications; rigorous) but these ideas vaguely convey practices of STEM education and instruction (Gerlach, 2012). Interpretations of what

STEM mean vary by stakeholder (Breiner, Harkness, Johnson & Koehler, 2012). Educators tend to relate STEM education to authentic problem based instructional tasks, where learners engage in scientific inquiry (Roehrig, Moore, Wang, & Park, 2012). Researchers often perceive STEM education as the integration of the disparate fields, where a problem-solving task connects the diverse sources of knowledge and bridges the conceptual applications of information in ways that mirror activities employed by scientists in the real-world (Hansen & Gonzalez, 2014). For institutions providing funding, STEM education is perceived as the mechanism through which our national workforce can become strengthened (National Science Foundation, 2015; National Research Council, 2015). National research institutions describe STEM as the means through which the U.S. economy and standards of living will become improved, as it produces high quality, knowledge-intensive jobs; STEM education thus grooms individuals to fill these jobs (National Academy of Sciences, National Academy of Engineering, & Institute of Medicine, 2007; Landivar, 2013). Parents often perceive STEM education as an innovative instructional approach that, while creative and perhaps even engaging to their children, does not seem to lead to the same learning outcomes as traditional math and science pedagogies (Breiner, Harkness, Johnson & Koehler, 2012). Students, at the core of STEM instruction, have been groomed to perceive STEM education as an outlet to reaching educational and professional success (Gerlach, 2012). These competing ideas, while related in some ways, contribute to confusions surrounding the essence of STEM and the depth and breadth of its reach.

The STEM Workforce

In today's workforce industry, the most widely available, highest paying jobs are predominantly in STEM fields. STEM occupations make up 1 in every 10 jobs in the United States, with STEM wages amounting to nearly twice the U.S. average (Jones, 2013). From 2008 through 2018, STEM occupations are projected to grow by 17 percent, compared to 9.8 percent for non-STEM occupations (Langdon, McKittrick, Beede, & Khan, 2011). The top ten bachelor's degree majors with the highest median earnings are all fields within STEM (STEM Education Coalition, 2016). Those employed with STEM jobs typically earn 26 percent more than those employed in non-STEM occupations (Langdon et al., 2011). Controlling for degree-type, at all levels of educational attainment, those with STEM jobs earn 11 percent higher in wages compared to those with the same degree in other occupations (Thomasian, 2011). Workers in STEM occupations experience lower unemployment rates than those in other fields (Langdon et al., 2011). STEM occupational openings outnumber unemployed persons about two to one (STEM Education Coalition, 2016). Looking at job requirements in particular, STEM competencies are required for occupations both within and outside of STEM (National Education Council and Office of Science and Technology Policy, 2015). About 20 percent of all jobs require higher-level knowledge in some branch of STEM (Thomasian, 2011).

While there is no objection to the STEM workforce's growth, breadth, or impact, differences in understandings of the composition and characteristics of the STEM workforce, and the "varied, dynamic career pathways enabled by STEM knowledge and skills," hinder analyses and conversations relevant for continued advancements (National

Science Board, 2015, p.1). One of these anomalies is defining the STEM workforce. The STEM workforce has been defined in diverse ways, depending on context, and consists of multiple sub-workforces based on some combination of factors relating to field of degree, occupational field, and education required (National Science Board, 2015). There is no standard definition of what constitutes as STEM, a STEM job, or even the STEM workforce; instead, definitions tend to be locally determined (Thomasian, 2011).

The Department of Professional Employees (2016) organizes STEM occupations into three main clusters: computer and mathematical occupations; architecture and engineering; and life, physical, and social sciences. When outlining STEM disciplines that are supported under initiatives aimed at addressing the need for a high quality STEM workforce, the National Science Foundation (NSF) identified the following areas: Biological sciences (except medicine and other clinical fields); Physical sciences (including physics, chemistry, astronomy, and material sciences); Mathematical sciences; Computer and information sciences; Geosciences; Engineering; and Technology areas associated with the preceding disciplines (e.g., biotechnology, chemical technology, engineering technology, information technology (NSF, 2016).

The Occupational Information Network (O*NET) defines STEM occupations as those that entail "planning, managing, and providing scientific research and professional and technical services (e.g., physical science, social science, engineering) including laboratory and testing services, and research and development services" (O*NET, n.d.). In addition, O*NET classifies many architectural occupations under engineering and technology, while professions like anthropologists, ethnic and cultural studies teachers, economists, historians, sociologists, and political scientists are cataloged under science and mathematics. The United States Census Bureau characterizes STEM professionals as those who work in computer and mathematical occupations, engineers, engineering technicians, life scientists, physical scientists, social scientists, and science technicians (Landivar, 2013).

Standard Occupational Classification (SOC) is a system used by all federal statistical agencies to classify workers into occupational categories (U.S. Bureau of Labor Statistics, 2016). The SOC policy committee developed two major STEM domains, which contain two subdomains each. The first domain includes core STEM occupations, while the second domain includes occupations that are dependent on STEM knowledge (Jones, 2014). The core domain, Science, Engineering, Mathematics, and Information Technology Domain, includes the following subdomains 1) Life and physical science, engineering, mathematics, and information technology occupations; and 2: Social science occupations. The second domain, Science- and Engineering-related Domain, includes 1) Architecture occupations, and 2) Health occupations as subdomains. Each STEM occupation can be further categorized into five different types of occupations. These include A) Research, development, design, or practitioner occupations; B) Technologist and technician occupations; C) Postsecondary teaching occupations; D) Managerial occupations; and E) Sales Occupations.

When research examines STEM jobs, science, technology, engineering, and mathematics positions are most consistently represented, but some studies also include management and sales in STEM fields (Thomasian, 2011). There are institutions that include large fields like health sciences, architecture, and agriculture within STEM, while others choose to exclude them (Koonce, Zhou, Anderson, Hening, & Conley, 2011).

When speaking of STEM professionals, there are entities that extend this group to include STEM educators, social scientists, healthcare professionals, and economists, while others would argue that these professions do not belong (Thomasian, 2011). Further, some conceptualize STEM as subject-matter driven instead of task specific, so managers, teachers, practitioners, researchers, and technicians are often included as STEM professions when they entail engaging in STEM-related activities (Landivar, 2013). Finally, while many individuals argue that STEM professionals and industries are over-represented, others make the point that research tend to under-represent positions that involve STEM-knowledge (Thomasian, 2011), an added level of complexity to this already complicated matter.

It is clear that there are many differences in how the STEM workforce is defined. Differentiations in the identification of professions included within STEM are also apparent. Even more pronounced are the areas of overlap between and among STEM classifications. Some conceptualize STEM as task specific, where the STEM taxonomy is characterized by the anatomy of the job description. Others tend to focus on levels understanding, where inclusion in STEM is dependent on whether the foundation of a job is built on STEM-related knowledge. The Standard Occupation Classification STEM taxonomy most successfully bridges these two ends of the spectrum together. SOC has the most comprehensive STEM definition, and addresses the complexities involved in the categorization process. The two major domains are distinguished by core STEM occupations and those occupations that require STEM-knowledge. This classification strategy speaks to the inclusion criteria that most often cause conflict when defining STEM occupations. The core domain is further sorted to identify STEM occupations that can be described as traditional, technical STEM fields, and then those that are used to make contributions to STEM understandings through a social science lens, another differentiating component among stakeholders. The STEM-related knowledge domain encompasses those areas whose inclusion and/or exclusion typically depended on perspective regarding the breadth assigned to STEM. These include architecture and health sciences.

Overall, it seems that the ways in which STEM occupations are defined are based on the purpose for classification and/or examination. Exhaustiveness or refinement of the STEM workforce, STEM occupations, and STEM professionals come down to what is trying to be fundamentally understood. Essentially, due to its extensiveness, the SOC taxonomy can be used to gain the most holistic perspective. Therefore, it was most fitting that I utilized the Standard Occupation Classification system as the framework for identifying careers inclusive of the STEM workforce.

As described earlier, there are often differences between STEM education and the STEM workforce, including the types of disciplines that are inclusive to each sector, respectively. Within education, disciplines included within STEM are typically those related to the four core domains, i.e., science, technology, engineering, and mathematics (Breiner et al., 2012; Gerlach, 2012). Using the Classification of Instructional Program codes developed by the National Center for Education Statistics (2010), majors in the following areas will be classified as STEM: computer and information sciences and support services; engineering; biology and biomedical sciences; mathematics and statistics; military technologies and applied sciences; physical sciences; science technologies/technicians; and natural resources and conservation. These major areas align with SOC, as they offer a strong foundation in core STEM areas, while also allowing for application to disciplines requiring STEM-related knowledge.

Trends in STEM higher education

Understandably, the composition of the STEM workforce is positively associated with the demographics of STEM college graduates, as having a STEM background facilitates STEM employment (Landivar, 2013). Analyzing the distribution of STEM degrees among college graduates from 2011, women accounted for 53 percent of all college graduates, but only 41 percent of STEM degrees (U.S. Census, 2012). Women earned about 34 percent of computers, mathematics, and statistics degrees; 45 percent of biological, agricultural, and environmental sciences degrees; almost 38 percent of physical and related science degrees; about 70 percent of psychology degrees; 48 percent of social science degrees; and 16 percent of engineering degrees (U.S. Census, 2012). Looking at race, 71 percent of STEM degrees were awarded to Whites, 14 percent of graduates were Asian, and about seven percent of degrees were awarded to both Blacks and Latinos each (U.S. Census, 2012). Additionally, while Native Americans account for approximately two percent of the population (U.S. Census, 2010), they earn only 1 in 150 of bachelor's degrees awarded in STEM (Smith, Cech, Metz, Huntoon, & Moyer, 2014).

While these statistics represent those who have gone on to complete their program of study, STEM retention is a major concern (PCAST, 2012). Factors associated with STEM attrition include students' demographic characteristics; precollege academic preparations; type of institution; and STEM course-taking and performance (i.e., intensity of course-taking, types of math courses, and level of success in STEM courses, all during the first year) (Chen, 2013). High STEM attrition is a significant hindrance to meeting the goal of strengthening our STEM workforce to becoming a highly qualified system composed of a literate, competent, and innovative population of STEM professionals. Only one in five college students in STEM majors felt that their K–12 education prepared them well for their STEM college courses (Microsoft Corporation, 2011). Less than 40 percent of students entering a STEM major at the start of college complete a STEM degree (STEM Education Coalition, 2016). Women and minorities have disproportionately high attrition rates, resulting in large gaps in STEM degree completion (Anderson & Kim, 2006). The retention numbers are most troubling for underrepresented minorities, where a staggering 16 percent continue on to earn a STEM degree (College Board, 2016).

It is projected that increasing overall retention from 40 percent to just 50 percent would generate three-quarters of the one-million STEM graduates needed over the next decade (PCAST, 2012). It is maintained that retaining STEM majors is the “lowest-costing, fastest policy option” to supplying the amount of STEM professionals required to meet the nation’s economic and social well-being needs (PCAST, 2012, p. 1). As a result, interventions are being targeted at the post-secondary level. Common strategies being implemented include trying to attract students to STEM college courses through improved, inspiring teaching practices; creating a welcoming atmosphere of a community of STEM learners; and providing support to students facing mathematical challenges (PCAST, 2012).

While these initiatives are cost-efficient in terms of addressing the urgency of populating the workforce with greater numbers of STEM professionals today, it is equally important that actions are taken that might have longer lasting and potentially more abundant effects, rather than focusing solely on those that immediately provide short-term outcomes for true reform (Fairweather, n.d.). Piecemeal educational solutions are rarely proven to be successful in the long run (Darling-Hammond, 2010). Further, interventions targeted at building interest and proficiency in STEM are recommended to be introduced during early school years (Cotabish, Dailey, Robinson, & Hughes, 2013). Early student engagement along STEM pathways results in an increased likelihood of a stronger STEM foundation, higher self-efficacy beliefs, and heightened STEM goal expectations (Early Childhood STEM Working Group, 2017). Furthermore, students deciding to pursue a STEM career by 8th grade are 3.4 times more likely to persist than those who make the same decision at a later period in their lives (Tai, Liu, Maltese, Fan, 2006).

It is important to note that the implementation of techniques proposed by the President's Council of Advisors on Science and Technology (2012) alone will continue to perpetuate underrepresentation in STEM, as these types of interventions are being targeted at those that have already chosen STEM majors at the start of college. This is problematic because women, Blacks, and Latinos are entering STEM at much lower rates (Shapiro & Sax, 2011; Wang, 2012). If these populations aren't even entering STEM, then despite interventions being introduced within postsecondary institutions, they will continue to be absent from STEM. Efforts need to be made that specifically target these populations prior to college entry to initially attract them into STEM in the first place. After targeted exposure- attraction- and recruitment-related practices are engaged, these post-secondary strategies might prove to be more meaningful for retention. It essentially comes down to whether the goal is to truly broaden STEM representation or simply increase the number of professionals within the STEM workforce.

Composition of the STEM Workforce

There has been a growing concern to increase the representation of diverse populations within STEM (PCAST, 2012; Committee on STEM Education, 2013; NSF, 2016). Increasing participation along STEM educational pathways would subsequently aid in reducing disparities that exist within the STEM workforce, where women, Blacks, Latinos, and Native Americans have historically remained underrepresented in STEM employment (Landivar, 2013; Smith et al., 2014). One of the major intentions of this effort is to support the national initiative to expand the STEM workforce (U.S. Department of Labor & Jobs for the Future, 2007). Women and minorities make up 70 percent of the college population, while only receiving approximately 45 percent of STEM degrees (PCAST, 2012). As a collective, women and minorities are viewed as an underrepresented majority that has the potential to be a substantial source of STEM professionals (PCAST, 2012). The issue in this thinking, however, is that focus seems to always center expanding the workforce. Attention is always paid to the cumulative numbers. Discussions rarely center on equitable implications relating to STEM workforce composition.

According to data from the American Community Survey of 2011 (i.e., the most recent and comprehensive data available on occupational demographics), six percent of the workforce consisted of STEM workers, which totaled 7.2 million individuals aged 25-64 (U.S. Census Bureau, 2012). Half of all STEM workers were in computer occupations, followed by 32 percent in engineering occupations, 12 percent in life and physical sciences, four percent in social sciences, and three percent in mathematical occupations. While women made up half the U.S. workforce, only 26 percent of STEM workers were women. Analyzing workforce trends, it is apparent that women's representation within STEM has increased since 1970 (U.S. Census Bureau, 1970-2010; U.S. Census Bureau, 2012). The only exception is in computer and engineering occupations, which has the most significant levels of underrepresentation. In fact, women's representation in computing was at its height in the 1990's, where it was at more than 32 percent. That number has since steadily declined to 27 percent. This also mirrors the decline in the number of women earning computer science degrees since the 1980's (Landivar, 2013). Similarly, women's growth in engineering has as remained stagnant since the 1990's, when it has grown from about 10 percent to a mere 13 percent. Together, computer and engineering occupations make up more than 80 percent of the STEM workforce—meaning women are least represented in the most abundant STEM sectors. Therefore, it is the significant underrepresentation within the computer and engineering sectors that most impact women's representation within STEM. Looking at participation percentages from the 1970's, women represented 17 percent of social scientists, 15 percent of mathematical and computer workers, 14 percent of life and physical scientists, and three percent of engineers. In 2011, women represented 61 percent of social scientists, 47 percent of mathematical professionals, 27 percent of computer workers, and 13 percent of engineers (Landivar, 2013).

Analyzing STEM workforce trends by race, Black, Latino, and Native American populations continue to be underrepresented in STEM, while Asians and Whites remain overrepresented (U.S. Census Bureau, 2012). White workers make up 67 percent of the

U.S. workforce, yet held 71 percent of STEM occupations. Similarly, Asians made up six percent of the overall workforce, but held 15 percent of all STEM jobs. Conversely, Blacks made up slightly less than 11 percent of the workforce, but only account for a little more than six percent of STEM. Latinos represent just under 15 percent of the overall workforce, but account for just 6.5 percent of STEM. Native Americans and Pacific Islanders make up more than five percent of the workforce, yet account for less than 2 percent of the workforce (Landivar, 2013).

Looking at changes since the 1970's, White representation in STEM has decreased from 94 percent in 1970 to 71 percent in 2011, but their representation in the overall workforce showed similar patterns (Landivar, 2013). On the other hand, Latinos share of the workforce has increased from 3 percent in 1970 to about 15 percent in 2011, but their representation in STEM has not increased at that same consistency (Landivar, 2013). Asians have always been overrepresented in STEM, where in 1970 they made up 2 percent of the STEM workforce, but only 1 percent of the overall workforce (Landivar, 2013). Today, they are even more overrepresented at 15 percent of the STEM workforce, while accounting for only six percent of the overall workforce (Landivar, 2013).

The next section presents Social Cognitive Career Theory, the framework used to guide this study. SCCT's background, central assumptions, core constructs, and key models will be discussed. Additionally, the application of SCCT to STEM career development will be presented.

Social Cognitive Career Theory Framework

Background and Roots

Over these last few decades, career development theories and research have shifted, emphasizing cognitive variables and processes that regulate career development (Borgen, 1991). The social cognitive perspective recognizes the relationships that exist between persons and their career-related contexts, cognitive and interpersonal factors, and self-directed and externally imposed influences, and identifies how these complex linkages affect career behaviors (Lent et al., 2002). Social Cognitive Career Theory (Lent, Brown, and Hackett, 1994) is a career development framework, largely based on Bandura's (1986) social cognitive theory. In addition, SCCT has been influenced by many other career development theories, and embraces key developmental discovers within vocational psychology (e.g., convergence and complementarity (Savickas & Lent, 1994), Holland's Theory of Career Choice (Holland, 1997)), psychological and counseling domains (e.g., Krumboltz's Social Learning Theory of Career Decision Making (Krumboltz, 1979; Krumboltz, Mitchell, & Jones, 1976)), Super's Career Development Theory (Super, 1990), Dawis and Lofquist's Theory of Work Adjustment (Dawis & Lofquist, 1984)), and the cognitive sciences (e.g., Barak's vocational interest (Barak, 1981), Eccles' Achievement-related decisions (Eccles, 1987), and Schunk's Self-efficacy and cognitive skill learning (Schunk, 1989)) (Lent et al., 2002). Amalgamating these diverse perspectives, SCCT can be thought of as an integrative framework that bridges the conceptual underpinnings central to career development. More specifically, SCCT identifies key variables that together create a comprehensive explanatory system and outlines the central processes by which these variables are linked together (Lent et al, 2002).

There are many advantages associated with considering the commonalities that exists among theories, rather than solely focusing on their differences. When describing the process engaged while building a unifying model, Lent, Brown, and Hackett (2002) discussed strategies proposed to be useful in their stride toward theoretical integration. These included: 1) bringing together conceptually related constructs (e.g., self-efficacy); 2) fully explaining outcomes commonly discussed in career theories (e.g., satisfaction); and 3) accounting for relationships among seemingly diverse constructs (e.g., self-efficacy, interests, abilities) (Hackett and Lent, 1992, p. 443). When creating this unified paradigm, Lent, Brown, and Hackett embedded these varied perspectives within the structure of Social Cognitive Theory, its most influential framework. The unique composition of Social Cognitive Career Theory that has resulted from these theoretical linkages allows for it application across diverse contexts.

Central Assumptions, Constructs, and Models

Social Cognitive Career Theory Assumptions

Underlying Social Cognitive Career Theory is two main assumptions. The first assumption is that there is a person-environment interaction, where components of the self-system are dynamic and situation-specific (Lent et al., 2002). This assumption highlights people's capacity to change, develop, and self-regulate, a view often neglected in other career theories' typological, trait-oriented conceptualization of person and environment variables. The second assumption is a triadic-reciprocal model of causality. SCCT postulates that there are "mutual, interacting influences among persons, their environment, and behavior," where each "affects one another bi-directionally" (Lent et al., 2002, p. 261). The components of this interlocking system include: personal attributes (e.g., internal cognitive and affective states, physical characteristics), external environmental factors, and overt behavior, which are separate from an individual's internal and physical qualities (Lent et al, 2002).

Social Cognitive Career Theory Concepts

Central to Social Cognitive Career Theory are three key theoretical constructs adopted from Social Cognitive Theory. These building blocks include self-efficacy (i.e., a person's beliefs about their ability to organize and perform actions required to attain selected performances), outcome expectation (i.e. a person's beliefs about the consequences of performing particular behaviors), and personal goals (i.e., a person's determination to engage in a particular behavior or effect a future outcome) (Bandura, 1986; Lent et al., 2002).

Self-efficacy is a dynamic, contextualized set of beliefs, and is acquired and modified via four primary sources of information (Lent et al., 2002). These four learning experiences include personal performance accomplishments, vicarious learning, social persuasion, and physiological and affective states (Bandura, 1997). Successful experiences with task involvement leads to heightened self-efficacy beliefs. In contrast, negative learning experiences within a particular performance domain lessen a person's self-efficacy.

Outcome expectations are also influenced by learning experiences, but in a slightly different manner than self-efficacy. Learning experiences shaping outcome expectations include appraisal of outcomes received after past performances, observing outcomes experienced by others, and taking notice of self-generated outcomes, and how they are perceived by others (Lent et al, 2002). Beliefs regarding extrinsic reinforcement, self-directed consequences, and outcomes following activity performance are examples of the types of outcome response beliefs a person might imagine.

Goal setting is key to self-empowerment. Goals represent a person's exhibition of personal agency as they engage in the process of controlling and directing their own behaviors (Lent et al, 2002). Together, self-efficacy, outcome expectation, and personal goal setting interact in interconnected, complex ways, and results in the self-regulation of one's behavior.

Social Cognitive Career Theory Models

Social Cognitive Career Theory presents career-related interest, choice, and performance through three interrelated models. It is important to note that Lent, Brown, and Hackett (2002) hold that SCCT and SCCT models are conceptually and developmentally applicable to academic-related processes as well. This is essential, as academic and career related pursuits often act in tandem. There is a natural progress during the school-to-work transition and obvious overlaps between academic and career development. As such, there is substantial usefulness in bridging models of academic and career development, too (Lent et al., 2002)

Central to this study are the interest and choice conceptual frameworks. The Interest Model, which serves as the foundation of the interlocking models, "emphasizes both the experiential and cognitive factors that give rise to career-related interests, while tracing the role of interests in helping to motivate choice behavior and skill acquisition" (Lent et al., 2002, p. 265). Interest is formed for activities that are believed to result in valuable outcomes or regarding tasks for which we believe we are competent. In contrast, we do not develop interest in domains that are anticipated to result in negative outcomes. When we become attracted to certain activities and start to develop positive interests, we begin to form goals surrounding future and continued involvement. Accumulated achievements resulting from activity involvement then influence beliefs regarding self-efficacy and outcome expectations. This cycle continues to be iteratively engaged throughout the lifespan.

In summary, the interest model asserts that an individual's self-efficacy and outcome expectation regarding task involvement has a direct effect on the subsequent cultivation of their interests. Furthermore, developing interests promote goal formation for activity involvement. These goals then translate to increased likelihood of activity engagement. Finally, attainments gained from activity engagement form a feedback loop, which either maintains or modifies self-efficacy and outcome expectations, thus interest, and so forth.

SCCT recognizes that social cognitive influences do not exist in a vacuum, and instead interact with important person and contextual variables to shape career-related outcomes (Lent et al., 2002). SCCT's Choice Model emphasizes those person, contextual and learning influences on choice behaviors (Lent et al., 2002). Moreover, goals and actions that were referred to in general terms within the Interest Model now characterize career-related goals and the actions required to implement them in the Choice Model. Integrated, SCCT's Interest and Choice Models offer a "conceptual framework for understanding the developmental continuity between the evolution of basic vocational interests and their eventual translation into career-relevant choices" (Lent et al., 2002, p. 272).

An important component of SCCT's Choice Model is the inclusion of contextual influences. These can be thought of as "structures of opportunity" perceived as being provided by (or lacking from) the environment. (Lent et al., 2002, p. 274). There are two types of opportunity structures identified within SCCT. These include distal, contextual influences (e.g., exposure to role models, opportunities for development, socialization processes) and proximal influences (e.g., sociostructural barriers, systems of support). Figure 3 below presents relationships that are hypothesized by SCCT to exist among social cognitive, person, and contextual variables.

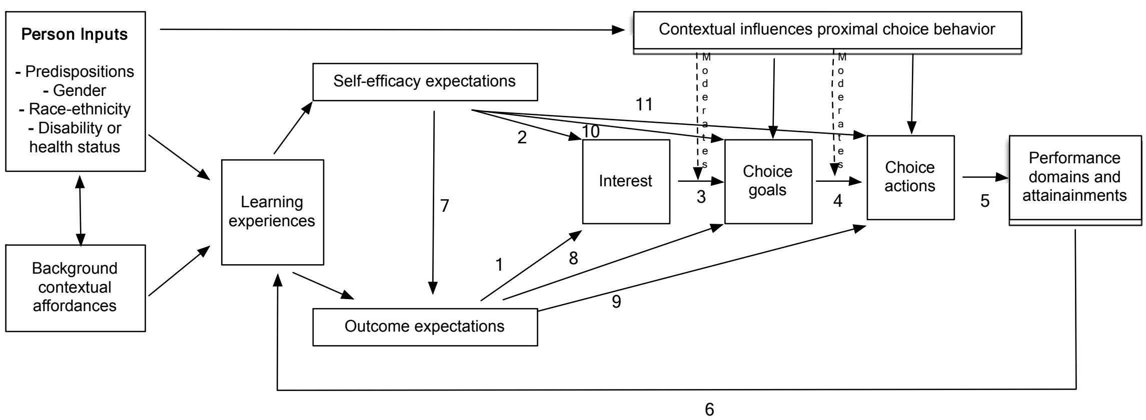


Figure 3. *Model of Person, Contextual, and Experiential Factors Affecting Choice-Related Behavior.* (Lent, Brown, and Hackett, 1993)

In their conceptualization of the career development process, Lent, Brown, and Hackett (2002) hypothesized the following relations: A) Self-efficacy and outcome expectation promote career-related interests (paths 1 and 2); B) Interest then serves as an influence on goals (path 3); C) Goals stimulate actions designed to implement one's goals (path 4); D) Goal-related actions lead to performance experiences (path 5); E) Outcomes aid in the modification or solidification of self-efficacy and outcome expectations (path 6) and thus redirects or further nurtures choice behaviors; F) Life's unpredictability may deter an individual's interests in pursuing a vocational path, therefore self-efficacy and outcome expectations may directly influence career goals and actions (paths 8-11); G) Opportunity structures moderate relationships from interest to goals and from goals to action (dotted paths); and H) Environmental conditions can exert direct effects on choice formation and implementation (solid lines from contextual variables to goals and actions) (p. 273-276).

Social Cognitive Career Theory and STEM Career Development

Social Cognitive Career Theory has been applied to diverse disciplines and contexts, and serves as an appropriate framework for understanding STEM career choice (Lent, Brown, & Hackett, 1994, 2000). A number of studies have been conducted that use SCCT to understand STEM academic (e.g., Betz & Hackett, 1983; Hackett, Betz, Casas, & Rocha-Singh, 1992; Lent, Lopez, & Bieschke, 1993; Lent, Lopez, Lopez, & Sheu, 2008; Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Wang, 2013; Garriott et al., 2014) and career (e.g., Navarro, Flores, & Worthington, 2007; Garriott et al., 2013; Chachashvili -Bolotin, 2016) choices. Given the nature of the SCCT framework (i.e., its presentation as interlocking models), most research utilizing this theoretical perspective employ structural equation modeling statistical techniques to understand the relationships among constructs (e.g., Turner, Steward, & Lapan. 2004; Navarro, Flores, & Worthington, 2007; Mills, 2009; Garriott, Flores, & Martens, 2013; Wang, 2013; Garriott et al., 2014; Nugent et al., 2015).

STEM-oriented SCCT studies vary in composition and focus. Study populations range from middle school (e.g., Navarro, Flored, & Worthington, 2007), to high school students (e.g., Garriott et al, 2014), and postsecondary school (e.g., Garriott et al., 2013), with minimal studies longitudinally examining career development across educational levels (e.g., Wang, 2013). While most research utilizes predominately White samples, some studies center particular racial/ethnic minority groups (e.g., Allima-Brissett, 2010), and a few even investigate potential subgroup differences (e.g., Wang, 2013). Studies vary in their disciplinary focus, with some examining STEM as a whole (e.g., Chachashvili-Bolotin, Milner-Bolotin, & Lissitsa, 2016), most simultaneously investigating math and science domains (e.g., Turner, Steward, & Lapan, 2014), and others only examining at a single STEM discipline (e.g., Luse, Rursch, & Jacobson, 2014).

Overall, findings have consistently proven SCCT to be predicative of STEM career choice (e.g., Gainor & Lent, 1998; Luse et al., 2014; Nugent et al., 2015), but depending on context, some paths have shown to be insignificant (e.g., Garriott et al., 2013; Chachashvili-Bolotin, Milner-Bolotin, & Lissitsa, 2016). The most consistently supported hypothesized path is the positive relation between self-efficacy and outcome expectation. The same holds for positive relations between self-efficacy and outcome expectation each to vocational interests (e.g., Foud & Smith, 1996; Lapan, Shaughnessy, & Boggs, 1996; Bishop & Bieschke, 1998; Gainor & Lent, 1998; Lent et al., 2005; Turner et al., 2004; Nugent et al., 2007). Other paths were also consistent, but at slightly lesser rates. These included positive relations between vocational interest and choice goals and actions (e.g., Gainor & Lent, 1998; Fouad & Smith, 1996; Lapan, Shaughnessy; Lent et al., 2005) and positive relations between contextual support and barriers to career choice (e.g., Lent et al., 2005).

A major limitation of research of SCCT within the context of STEM is that it has primarily been conducted using predominately White populations, with little consideration for potential differences that might exist with samples comprised of racial minorities. Furthermore, due to SCCT's extensiveness, most research only examine key hypothesized paths, instead of the exploring the entirety of the Choice Model. As such, very few studies have investigated the role of learning experiences within career development (e.g., Gainor & Lent, 1998, Lopez, et al., 1997; Dickinson, 2007; Garriott et al., 2014). Similarly, few studies examine the direct affect of contextual affordances on career goals and choice, and rarely any ever examine the moderating effects of contextual supports and barriers on interests-goals and goals-actions relations (Dickinson, 2007). Finally, studies typically use institution-specific samples and cross-sectional designs (Lent et al., 2010; Wang, 2013).

This research addressed these gaps, as it explicitly attempted to understand the role of learning experiences and contextual supports and barriers in STEM career development; examined potential differences that might exist based on racial, gender, and class subgroups; and utilized nationally representative longitudinal data. The next section will present frameworks (i.e., Social Cognitive Career Theory and Intersectionality) that were used to critically examine STEM career development. These frameworks help to makes sense of how identity categories, like gender, race/ethnicity, and socio-economic status, shape an individual's STEM career development.

Critical Frameworks

Social Cognitive Career Theory

Lent et al. (2002) critiqued the manners through which career theories understood the role of race and gender in career development, thus provides an alternate approach for analyzing how these constructs shape this process. Historically, race and gender have been discussed in descriptive terms, where differences between group-related outcomes were simply documented. Hackett and Lent (1992) noted that a more meaningful approach would be to identify the processes through which race and gender affect career development. From a SCCT perspective, race and gender are deeply embedded characteristics of a person's socially constructed world, rather than mere assigned biological traits. Further, their relationships to career development originate from the responses induced by social-cultural environments and from their connections to "the structure of opportunity within which career behaviors transpires" (Lent et al., 2002, p. 268). Thus, rather than concentrating on sex and race, we should move to examine gender and ethnicity as "socially constructed concepts that include the psychological, social and cultural experience" of sex and race, respectively (Fassinger, 2000; Lent et al., 2002, p. 268). The same holds true for other socially constructed identity categories as well (e.g., socio-economic status).

Focusing on the social, cultural, and economic conditions that shape learning opportunities for individuals, experienced interpersonal reactions, and outcomes individuals anticipate based on their gendered, racial, and socio-economic characteristics, can lead to a better understanding of the structural biases associated with academic- and career-related access and opportunities (Lent et al., 2002). As such, SCCT views sociostructural factors like race, class, and gender from a social constructivists perspective, which allows for a systems-level, critical examination of these constructs within the context of career development.

Intersectionality

Coined by Crenshaw (1989, 1991), intersectionality is a methodological approach that allows for the analysis of multiple social categories simultaneously. It is used to examine socially constructed identity categories, like race, gender, ethnicity, socio-economic status, ability, and other “dimensions of difference that shapes the construction and representation of identities, behavior, and complex social relations” (Dill, 2002, p.5). McCall (2005) describes intersectionality as a “central category of analysis” in and of itself, and defines it as “the relationships among multiple dimensions and modalities of social relations and subject formations” (p. 1771).

An intersectional lens, or any other critical methodology, is rarely used within quantitative research to make meaning of phenomena being understood (Else-Quest & Hyde, 2016). Instead, when looking at race, for instance, most racial/ethnic minorities are often grouped together to create one racial category called ‘under-represented minorities’ (Lord et al., 2009). This negates the truth that each group may encounter differing lived experiences, which then shape the nuances of their reality (Lord et al., 2009). These complex processes are often the result of social constructions permeated through the socio-political systems within which we operate. Finally, most quantitative research tends to focus on identity categories like race and gender separately, failing to consider their intersection (Ro & Loya, 2015). Individuals are more than a single identity, and conducting analyses in such a way is problematic. It falsely assumes that a singular characteristic translates to identical backgrounds, experiences, and outcomes for all individuals sharing that identity (Whittaker & Montgomery, 2012).

Intersectional Approaches

McCall acknowledged the difficulties associated with intersectionality, particularly with regard to its use as a methodology. She offered three intersectional approaches (i.e., anticategorical complexity, intracategorical complexity, and intercategorical complexity) as alternate strategies for carrying out this methodological technique (McCall, 2005). Each of these approaches comprises different underlying assumptions, understandings, and uses of analytical categories.

The technique most applicable to this research is intercategorical complexity. This categorical approach recognizes that relationships of inequality exists among already established social groups, thus requires researchers to temporarily adopt existing analytical categories to record those relationships of inequality. These can be viewed as researchers' "anchor points" of analyses. Next, scholars are instructed to alter the configuration of inequality along multiple and conflicting dimensions (McCall, 2005, p. 1773). From this perspective, focus centers the complex relationships among multiple social groups within and across analytical categories, where "the subject is multi-group, and the method is systematically comparative" (McCall, 2005, p. 1786). This means that each category must be cross-tabulated with all others being examined in the analysis. For instance, if gender were the social group, males and females would be the two categories compared (depending on how you understand gender to operate and exist). Additionally, if the examination were extended to include race as well (e.g., White, Black, Latino), then there would be six groups requiring analysis. If socioeconomic status were incorporated (e.g., high, medium, and low), then 15 categories of analysis would need to be conducted, and so forth. It is also important to note that there are more subgroups than the 15 in the above scenario if you consider the multiple social group subsets (e.g., Black women, middle class Latinos) that also result.

Limitation of this approach lies in the abundance and complexity that could result from the disaggregation and cross-classification among multiple groups (McCall, 2005). In addition, when the sample sizes of particular identity categories are small, you are limited in the depth of intersectional analysis allowed. Size- and significance-related shortcomings may contribute to limited analyses of overlap conducted within quantitative social science research (McCall, 2005).

Summary

This research investigated the process by which high school students made the choice to engage in STEM-oriented career behaviors. It examined factors contributing to students' development of STEM career intentions, and ultimately, their selection of a STEM major during college. Review of the literature highlighted similarities and differences in how STEM is operationalized in diverse contexts and paradigms. It also shed light onto the disparities that exist in STEM representation with regard to both STEM education and the STEM workforce. Finally, theoretical frameworks were presented, which guided research endeavors and aided in the conceptualization of how the overlap among diverse identity categories were situated in the context of STEM career development. Chapter three will present an overview of data used, detailed descriptions of analytical models developed, and procedures engaged during all methodological practices employed.

Chapter 3: Methodology

This research examined the career development process of high school students using a Social Cognitive Career Theory framework. This chapter will present the methodological practices employed in this investigation. Understandings of the complex relationship among factors contributing to students' decision to pursue STEM were gained through the use of structural equation modeling statistical techniques. Additionally, multi-group analyses were engaged to identify potential group differences.

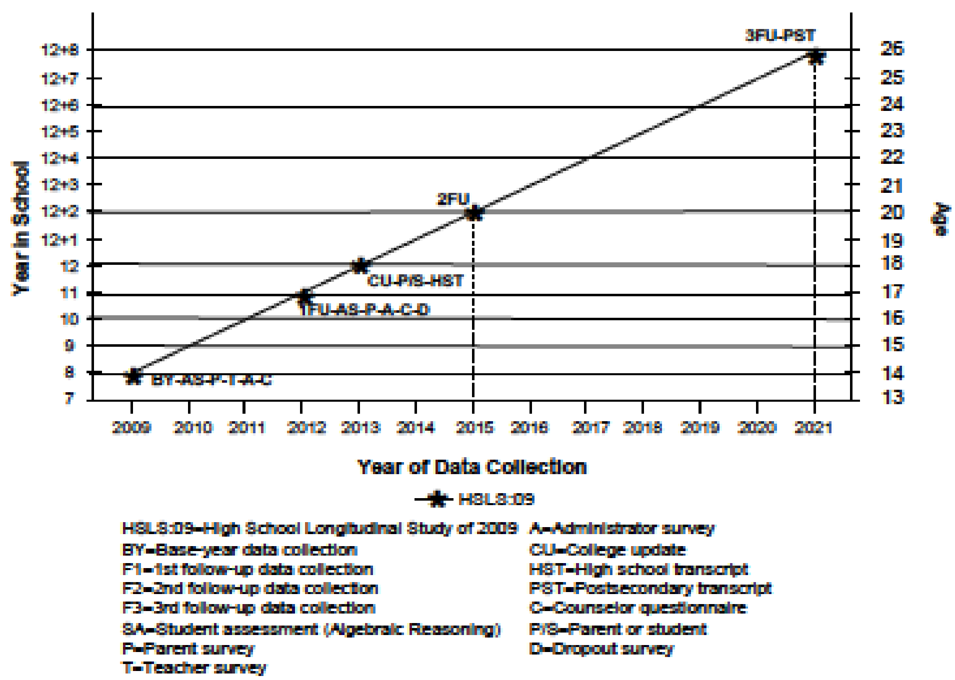
This chapter begins by describing High School Longitudinal Study of 2009, the extant data source used for this study. Then, research questions and associated hypotheses are outlined. Detailed information is provided regarding all study measures. Next, through combining tenets of Social Cognitive Career Theory, information found in the literature, and accessible variables within the data, a conceptual model is proposed. Subsequently, an analytical model is presented. Finally, detailed descriptions of all analytical procedures employed are discussed.

Research Methods

This research intended to understand high school students' STEM career development. As such, it examined the relationship among factors relating to students' decisions to participate in STEM-related activities; students' development of STEM beliefs; students' intentions to pursue STEM careers; and subsequently, students' selection of STEM majors. Structural equation modeling statistic techniques were used to understand the influence of learning experiences, environmental supports and barriers, and constructs core to Social Cognitive Career Theory on students' STEM career behaviors. Longitudinal data were used to investigate the effects of these cognitive, psychological, and environmental variables on students' STEM career development across three waves of data collection. Finally, intersectional approaches were engaged to understand differences in STEM career behaviors when considering the overlap among individuals' diverse socio-demographic characteristics and backgrounds. An overview of the data used in this study is described below.

Overview of Data Source

This study employed Structural Equation Modeling statistical techniques to gain insight into high school students' STEM career development process. Data for this research came from the High School Longitudinal Study of 2009 (HSLS:09) (Ingles et al., 2015). HSLS:09 is a nationally representative, longitudinal study that followed approximately 24,000 high school students (Ingles et al., 2015). The study population included a representative sample of 944 high schools, each from which approximately 25 ninth-grade students were randomly selected to participate (Ingles et al., 2015). Selected schools included both public and private institutions; all were required to have a 9^{th} and 11^{th} grade level. The study includes student- and school-level data, with surveys being conducted with students, parents, math and science teachers, school administrators, and school counselors (Ingles et al., 2015). To date, three waves of data collection have been conducted, including the 2009 Base Year, which was fall of the students' 9th grade year; a 2012 Follow-up, which was spring of what would have been students' 11th grade year; and a 2013 Update, which was spring of students' expected graduation year (Ingles et al., 2015). The fourth wave of data, the Second Follow-up, is currently in collection. In addition, students' high school academic transcripts were collected, which provides a record of courses taken, credits accrued, and grades earned (Ingles et al., 2015). Finally, a mathematics assessment was administered to all students during the 2009 and 2012 data collections, which measured student achievement in algebraic reasoning (Ingles et al., 2015). Figure 4 below displays the entire data collection timeline for HSLS:09.



Source: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. High School Longitudinal Study of 2009 (HSLS:09) Base Year.
Figure 4. *Longitudinal design for HSLS:09 ninth-grade cohort from 2009-21*

At its core, HSLS:09 is designed to observe adolescents' transitions through major stages of life (Ingels et al., 2011). It begins with monitoring students' high school experiences and continues on to observe their post-secondary journey, including continued educational pursuits, workforce participation, and other roles and responsibilities taken on during the adult years. The overall purpose of HSLS:09 is to explore the transition between secondary and post-secondary plans, and the subsequent evolution of those plans; the paths into and out of STEM; and educational and social experiences affecting those shifts (Ingels et al., 2011). Essentially, there are three major foci of HSLS:09. These include understanding students' trajectories from the beginning of high school into postsecondary education, the workforce, and beyond; understanding students' major and career pursuits, and when, why, and how those decisions are made; and understanding how students come to choose STEM majors and careers (Ingels et al., 2011).

The use of these data within the context of this study was both relevant and appropriate, as each area of concentration identified within HSLS:09 greatly aligned with core points outlined in this study's purpose. More specifically, HSLS:09's investigation into student trajectories from high school to postsecondary education, the workforce, and beyond parallels this study's intent to understand high school students' career development process, which inherently includes these same fundamental developmental periods. Further, HSLS:09's attention to major and career decisions and the process by which that happens aligns with this study's emphasis on understanding the relationship between those person, cognitive, psychological, and environmental factors that may influence students' academic and career pursuits. Finally, HSLS:09's attention to students' choice of STEM-related courses, majors, and careers, more specifically, gets at the larger objective driving this research—increasing student participation along STEM pathways.

High School Longitudinal Study's comprehensiveness allowed for an in-depth, empirical understanding of students' self-efficacy, outcome expectations, interests, and choices related to STEM, both cross-sectionally and across time. Further, it allowed for an examination of students' STEM-oriented beliefs and behaviors during high school, and provided insight into how psychological and behavioral states of being translated into particular actions at the post-secondary sector and, potentially, beyond. In addition, given the robustness of information collected, particularly from teachers, administrators, and guidance counselors about the nature of the school environment, HSLS:09 allowed for an investigation into how school-level variables influenced individuals' academic- and career-oriented decisions. HSLS:09 permitted the conduct of both individual- and systems-level analyses. Essentially, with this data set, I was afforded the opportunity to understand students' STEM career development process, while simultaneously examining the context (e.g., systems, supports, barriers) with which this complex phenomenon was situated and, thus, inherently shaped by. Finally, because of its large-scale nature, HSLS:09 allowed me to conduct an intersectional analysis on core study constructs.

Research Questions and Hypotheses

Given the urgent call for an increase in STEM professionals, combined with the need to address the robustness of inequity present when viewing population trends of STEM participants, the following research questions and associated hypotheses were posed.

RQ1: Are there differences in students' STEM career intentions or STEM major selections, based on race/ethnicity, gender, or socio-economic status?

> H:1 There are differences in students' STEM career intentions and STEM major selections based on students' race/ethnicity, gender, and socio-economic status. More specifically:

(H:1:A) White and Asian students will report intent to pursue STEM careers and select STEM majors at higher rates than Latinos and Blacks.

(H:1:B) Male students will report intent to pursue STEM careers and select STEM majors at higher rates than female students.

(H:1:C) Students from higher socio-economic quintiles will report intent to pursue STEM careers and select STEM majors at higher rates than those from lower socio-economic quintiles.

RQ2: What is the relationship among cognitive, psychological, and environmental factors as related to high school students' intent to pursue a STEM career and selection of a STEM major?

Hypothesis 2 (H:2) There is a relationship among cognitive, psychological, and environmental factors, (i.e., those relating to students' past learning experiences; students' self-efficacy, outcome expectation, and interests; and school-related environmental supports and barriers), which influences high school students' intent to pursue a STEM career and selection of a STEM major.

H:2:A) Learning experiences (i.e., math aptitude, math and science identity, and STEM informal learning participation) directly influence math and science self-efficacy.

(H:2:B) Learning experiences (i.e., math aptitude, math and science identity, and STEM informal learning participation) directly influence math and science outcome expectations.

(H:2:C): Students' math and science self-efficacy has a direct, positive influence on intent to pursue a STEM career.

(H:2:D): Students' math and science self-efficacy has a direct, positive influence on selection of a STEM major.

(H:2:E) Students' math and science outcome expectation has a direct, positive influence on intent to pursue a STEM career.

(H:2:F) Students' math and science outcome expectation has a direct, positive influence on selection of a STEM major.

(H:2:G) Math and science interest has a direct, positive influence on intent to pursue a STEM career.

(H:2:H) Students' intent to pursue a STEM career has a direct, positive influence on STEM major selection.

(H:2:I) Environmental supports and barriers have a direct, positive influence students' intent to pursue a STEM career.

(H:2:J) Environmental supports and barriers have a direct, positive influence students' selection of a STEM major.

(H:2:K) Environmental supports and barriers have a direct, positive influence on the relationship between students' math and science interest and their intent to pursue a STEM career.

(H:2:L) Environmental supports and barriers have a direct, positive influence on the relationship between students' intent to pursue a STEM career and their selection of a STEM major.

RQ 3: Are there differences in how math-related core Social Cognitive Career Theory predictors (i.e., math- self-efficacy, outcome expectation, and interest) influence STEM career intentions and major selection, based on gender, race/ethnicity, or socio-economic status?

H3: There are differences in how math-related core SCCT factors influence STEM career intentions and major selections based students' gender, race/ethnicity, and socio-economic status.

Measures

This section describes variables that were included within the proposed STEM career development conceptual model. Endogenous variables, exogenous variables, mediating variables, and moderating variables will be reviewed. All variables, as well as a short description of how variables were measured, can be found in Table 1 on page 64.

Endogenous Variables

Within this model, there were two major outcomes: intent to pursue a STEM career and college major selection. Within STEM career development literature, both are regularly selected as endogenous variables, as both are viewed as key indicators of future STEM professional participation (Wang, 2013; Guo et al., 2015).

Intent to pursue a STEM Career

Intent to pursue a STEM career was measured by an item asking students, "What occupation do you expect to have at age 30?" (Ingels et al., 2014, p. A-52). For this item, student responses were coded based on the Occupational Information Network (O*NET) Taxonomy, which categorizes occupations into particular domains. Going further, a STEM sub-domain was created to specifically identify occupations that were relevant to the STEM disciples. The STEM sub-domain included six groupings, which were life and physical science, engineering, mathematics, and information technology occupations; social science occupations; architecture occupations; health occupations; split-across two sub-domains; and unspecified sub-domain. Occupations within the unspecified sub-domain largely consisted of life and physical scientists and technicians. For this study, occupational choices that fell under any of those categories, except social science occupations, were used to indicate students' expectation to engage in STEM career pursuits, as this research was interested in disciplines requiring core STEM knowledge at its foundation. According to the SOC taxonomy, the social sciences are distinct from what is traditionally thought of as core STEM subjects, and do not require STEM-related knowledge (U.S. Bureau of Labor Statistics, 2016). All other occupational groupings fit in one of these two categories of STEM career domains, thus closely align with how STEM careers were defined within the context of this research. As such, this HSLS:09 variable (X2STU30OCC_STEM1) was transformed from a nominal scale into a dichotomous variable, where intent to pursue a STEM career (1) represented students' expectation to have an occupation in life and physical science, engineering, mathematics, and information technology; architecture; health; those split into two sub-domains; or those within the unspecified sub-domain. Otherwise, it was concluded that students showed no intention of pursuing a STEM career (0).

STEM major selection

Next, STEM major selection was measured using an item that asks students, “What field of study or program will you be considering” (Ingels et al., 2015, p. B-15). Similar to the occupational taxonomy, college majors were categorized by Classification of Instructional Programs (CIP) codes. HSLS:09 created a dichotomously coded variable (S3FIELD_STEM), which further refined this classification to identify majors specific to STEM fields. Majors included those within computer and information sciences and support services; engineering; biology and biomedical sciences; mathematics and statistics; military technologies and applied sciences; physical sciences; science technologies/technicians; and natural resources and conservation. It is important to note that the social sciences, and disciples requiring STEM-related knowledge, were not included in HSLS:09’s STEM categorization (Ingels et al., 2015). Only core STEM subjects were identified. For this study, STEM major selection as an outcome was based on this dichotomously coded STEM field variable, with 1 representing a major selection within one of these fields, and 0 representing selection of a major in a different discipline or students’ indication of non-enrollment in college.

<u>Exogenous Variables</u>

Learning Experiences

Within the model, there were multiple variables that contextualized STEM career development. They accounted for the influence of students’ past learning experiences on vocational choice. Learning experiences as a model component followed from Social Cognitive Career Theory’s framework, as past learning experiences directly and vicarious impact a person's development of self-efficacy and outcome expectation. What this suggests is that when individuals encounter positive experiences in academic and/or career related activities and exhibit the aptitude needed to do well in specific academic and/or career domains, the likelihood that they will develop robust efficacy expectations and positive outcomes for these career pursuits are greatly increased (Lent et al, 2002). Further, it is improbable for individuals to develop interests in particular career and academic pursuits for which they may be very well-suited if they are not "exposed to compelling learning opportunities that promote ability-congruent efficacy beliefs and positive outcome expectations" (Lent et al., 2002, p.272). Within this study, exogenous variables capturing students' learning experiences included math achievement, math and science identity, and STEM informal learning participation. Those learning experiences (i.e., aptitude, identity, and informal learning) are deeply rooted in the literature as influencing career development more globally, and when STEM-oriented, impacting STEM participation more specifically (Martin, 2009; Alliman-Brissett & Turner, 2010; Duffy, 2010; Varelas et al., 2012; Ward et al., 2012; Lyon et al., 2013; Chachashvili-Bolotin et al., 2016).

Mathematics Aptitude

Students' score on the algebraic reasoning mathematics assessment was used to measure math aptitude. This assessment was designed to assess a cross-section of understandings representative of the major domains of algebra and the key processes of algebra (Ingels et al., 2014). Six domains of algebraic content (the language of algebra; proportional relationships and change; linear equations, inequalities, and function; nonlinear equations, inequalities, and functions; systems of equations; and sequences and recursive relationships) and four algebraic processes (demonstrating algebraic skills; using representations of algebraic ideas; performing algebraic reasoning; and solving algebraic reasoning) were included within the test specification.

The math IRT-estimated scale score (X2TXMSCR) was the variable used for this measure. X2TXMSCR is a criterion-referenced measure of aptitude (Ingels et al., 2014). The criterion is the set of skills defined by the HSLS:09 framework and represented by the 118 items in the HSLS:09 math item pool. The estimated scale score for math is an estimate of the number of items students would have answered correctly had they responded to all 118 items in the item pool. The ability estimates and item parameters derived from the IRT calibration can be used to calculate each student's probability of a correct answer for each of the items in the pool. These probabilities are summed to produce the IRT-estimated number-correct scale score.

A criterion-referenced score was used instead of a norm-referenced score because I wanted to use a pre-set standard of students' competence on mathematical concepts as opposed to a scoring system that compared students to overall population performance. A major reason contributing to this decision was that there may not have be equivalence across subpopulations due to a host of factors, including those relating to supports and barriers within the school environment, geographical locale, past preparation, and racial and socio-economic characteristics, to name a few. Each of these could have impacted a normative interpretation of math achievement, as there is a great deal of difference that can unfairly discriminate performance in this nationally representative sample. Finally, and most importantly, the intention of this study was to gain an understanding of the STEM career development process of high school students. Within educational measurement, test score generalization is documented as "a valuable attribute of criterion-referenced measurement" (Hambleton & Zaal, 1991, p. 9). Using a criterion-referenced score allowed for greater generalizability when compared against a norm-referenced score, as criterion-referenced approaches objectively measure relevant content domains, while norm-referenced techniques would be based on performance situated within the context of this specific cohort of students (Reynolds, Livingston, & Willson, 2010).

Math and Science Identity

Math and science identity were measured using composite variables (Ingels et al., 2014). Each composite variable was created using principal component analysis and standardized to a mean of 0 and standard deviation of 1. Scale values were only assigned to students who provided a full set of responses. Scales were developed using items that asked students their level of agreement—using a 4-point Likert-scale, ranging from strongly agree to strongly disagree—with statements about their math or science courses, respectively.

There were two items used as inputs to create the identity composite variable. Students were asked their level of agreement with the statements, “You see yourself as a math/science person” and “Others see you as a math/science person. (Ingels et al., 2014, p. E-21-E-22)” For this study, the HSLS:09 math identity (X2MTHID) and science identity (X2SCIID) composite variables were used to measure math and science identity, respectively.

STEM Informal Learning Participation

STEM informal learning participation was measured by the number of informal learning experience-types students participated within. Students were asked if they participated in different types of math and science activities, each of which were dichotomously coded (Ingels et al., 2014). Listed activities included math clubs, math competitions, math summer programs, math study groups, and math tutoring programs for mathematics-relevant informal learning, and science clubs, science competitions, science summer programs, science study groups, and science tutoring programs for science-relevant informal learning. These dichotomously coded variables were combined to create a continuous variable indicating overall science or math informal learning participation, respectively. Potential scores ranged from 0 to 5 each, which represented the number of informal experience types students participated in.

<u>Mediating Variables</u>

There were multiple variables within the model that mediated relationships. These model elements included math and science self-efficacy; math and science outcome expectation; and math and science interest. Each of these constructs was measured by a composite variable that had been created using principal component analysis. Scale values were only assigned to students who provided a full set of responses. Scales were developed using items that asked students their level of agreement—using a 4-point Likert-scale ranging from strongly agree to strongly disagree—with statements about their math or science courses, respectively. For each statement, the generic phrase 'math/science course' was customized to match the type of math/science class students indicated being enrolled in so that students knew which specific courses that particular question of the questionnaire was referring to.

Math and Science Self-Efficacy

Math and science self-efficacy are constructs directly following Social Cognitive Career Theory framework (Lent et al., 2002), which highlights the role of self-efficacy in career development. Rather than speaking of self-efficacy in general terms, the proposed conceptual model looked at math and science self-efficacy more specifically, as this research intended to understand the role of self-efficacy in students' construction of expectations, interests, goals, and decisions surrounding STEM participation.

The self-efficacy scale measured students' level of self-efficacy regarding their math or science courses, respectively (Ingels et al., 2014). This scale was developed using four items, which included, "You are confident that you can do an excellent job on tests in this course;" "You are certain that you can understand the most difficult material presented in the textbook used in this course;" "You are certain that you can master the skills being taught in this course;" and "You are confident that you can do an excellent job on assignments in this course" (Ingels et al., 2014, p. A-66-A-67) Math-self efficacy (X2MTHEFF) and science-self-efficacy (X2SCIEFF) were two separate composite variables within the dataset, and were utilized within the analytical model to measure math and science self-efficacy, respectively.

Math and Science Outcome Expectation

Math and science outcome expectation is a construct directly following Social Cognitive Career Theory framework (Lent et al., 2002), which highlights the role of outcome expectation in career development. Rather than speaking of outcome expectation in general terms, the proposed conceptual model looked at math and science outcome expectation more specifically, as this research intended to understand the role of outcome expectation in students' construction of interests, goals, and decisions surrounding STEM participation.

The outcome expectation scale measured students' expectations of the utility (as an outcome) of math or science courses, respectively (Ingels et al., 2014). Three items were used as inputs for this scale. The statement for each item began with, "What students learn in this course…" and continued with "is useful for everyday life;" "will be useful for college;" and "will be useful for a future career" (Ingels et al., 2014, p. A-80). Within the dataset, there were two variables that were used as a proxy for math outcome expectation (X2MTHUTI) and science outcome expectation (X2SCIUTI), respectively. Thus, each was utilized within the math or science associated analytical model.

Math and Science Interest

Math and science interest is a construct directly following Social Cognitive Career Theory framework (Lent et al., 2002), which highlights the role of interest in career development. Rather than speaking of identity in general terms, the proposed conceptual model looked at math and science interest more specifically, as this research intends to understand the role of interest formation in students' construction of goals and decision-making surrounding STEM participation.

The interest scale measured students' interest in their math or science courses, respectively (Ingels et al., 2014). Five items were used as inputs for this scale. The first three items asked levels of agreement with the statements, "You are enjoying this class very much;" You think this class is a waste of your time;" and "You think this class is boring" (Ingels et al., 2014, p. A-66). The fourth item asked students to select their favorite school subject. Finally, the last item asked students to select their rationale for taking the course. Within the data, math interest (X2MTHINT) and science interest (X2SCIINT) were two separate composite variables, and were used within *the* analytical model to measure math and science identity, respectively.

Moderating Variables

Environmental Supports and Barriers

The final aspect of the model identified environmental supports and barriers influencing student career development. The inclusion of these variables directly followed Social Cognitive Career Theory, which states that people's agency to freely make career choices is often limited due to the impact of environmental and other structural influences (Lent et al., 2002). Physical, social, cultural, and social features of the environment serve as (perceived and actual) structures of opportunity, and thus guide behavior through an individual's engagement in the cognitive appraisal process (Lent et al., 2002). While learning experiences influence self-efficacy and outcome expectation, these opportunity structures moderate those paths from interests to goals and goals to choice-related actions through affecting individuals' ability to transform between stages (Lent et al., 2002). If a person's environment is supportive, meaning the conditions are beneficial to their career pursuits as a result of ample supports and minimal barriers, they are more likely to navigate the process of interest formation, goal-setting, and action-taking. Conversely, those faced with environmental barriers that serve as obstacles to particular career pursuits are more prone to defer from those career-related processes (Lent et al., 2002). Within this study, informal STEM exposure, math and science teacher beliefs, and math and science teacher expectation may have been environmental supports or barriers depending on structures in place.

Informal STEM exposure

Informal STEM exposure was measured by the amount of activities engaged by the school to raise students' interest and achievement in math and science (Ingels et al., 2011). The list of potential STEM-related events included: Holding school-wide math or science fairs, workshops or competitions; Partnering with community colleges or universities that offer math or science summer programs or camps for high school students; Sponsoring a math or science after-school program; Pairing students with mentors in math or science; Bringing in guest speakers to talk to students about math or science; Taking students on math- or science-relevant field trips such as to a city aquarium or planetarium; Telling students about regional or state math or science contests, math or science web sites and blogs, or other math or science programs online or in your community; Requiring teacher professional development in how students learn math or science; requiring teacher professional development in increasing student interest in math or science; or something else. A scale was created that measured schools' level of informal STEM exposure, which totaled the different types of STEM opportunities offered. The potential score a school could receive ranged from 0-10, which represented the number of informal exposure activity types schools engaged.

Math and Science Teacher Beliefs

Math and science beliefs measured teachers' attitudes surrounding their teaching practices and students' learning potential (Ingels et al., 2011). Within the dataset, math teacher beliefs (X1TMEFF) and science teacher beliefs (X1TSEFF) were two separate composite variables, and were used to measure math and science teacher beliefs, respectively. Originally within the data, these scales were meant to represent teacher self-efficacy, but appeared to operationalize teacher attitudes toward their students rather than teachers' self-efficacy regarding their personal teaching practices. Therefore, it was appropriate to assign the label *teacher beliefs* to this scale. The teacher belief scale was created using principal component analysis. Each composite variable was composed of eight items as inputs. Only respondents who provided a full set of responses were assigned a scale value.

The items in this scale asked math and science teachers about their levels of agreement with statements as applied to their instruction or students' learning potential. Items included, "The amount a student can learn is primarily related to family background;" "If students are not disciplined at home, they are not likely to accept any discipline at school;" "You are very limited in what you can achieve because a student's home environment is a large influence on their achievement;" "If parents would do more for their children, you could do more for your students;" "If a student did not remember information you gave in a previous lesson, you would know how to increase their retention in the next lesson;" "If a student in your class becomes disruptive and noisy, you feel assured that you know some techniques to redirect them quickly;" "If you really try hard, you can get through to even the most difficult or unmotivated students;" and "When it comes right down to it, you really can not do much because most of a student's motivation and performance depends on their home environment" (Ingels et al., 2011, p. A-194-A-195).

Math and Science Teacher Perceptions of Expectation

Finally, math and science teacher expectations were measured using a scale variable that captured teachers' perceptions of math and science teachers' expectations at their school (Ingels et al., 2011). Within the dataset, math teacher expectation (X1TMEXP) and science teacher expectation (X1TSEXP) were two separate variables, and were used to measure math and science teacher expectation, respectively. Principal component analysis was used to create the teacher expectation composite variable. There were eight items that were used to create this scale. Items asked teachers to indicate their level of agreement with statements about math and science teachers at their school, respectively. The statement began with, "High school math/science teachers at your school…" and continued with, "set high standards for teaching;" "set high standards for students' learning;" "believe all students can do well;" "make expectations for instructional goals clear to students;" "have given up on some students;" "care only about smart students;" "expect very little from students;" and "work hard to make sure all students are learning (Ingels et al., 2011, p. A-181-A-182).

The table 1 below summarizes all variables included in the proposed career development conceptual model. All latent constructs and associated indicators are specified. *Model component* is the name of the construct present within the conceptual model. Components are categorized by variable type (i.e., endogenous, exogenous, mediating, or moderating). *HSLS:09 Survey Item Description* provides an explanation of the model components. Within this section of the table, all questionnaire items that were used to measure each component are listed. Further, details regarding the category of data are presented. If the endogenous variable is dichotomous, information about the binary output is provided. Similar details are provided for categorical and continuous scales. *[Labels]* are the names of the specific variables used as inputs to create scale variables. Finally, *HSLS:09 Variable Name* depicts the name assigned to the variable within the dataset. If a particular construct (model component) is measured by combining more than one variable, multiple variable names will be listed.

It is important to note differences in the naming conventions of HSLS:09 variables. The following patterns were used to name variables (Ingels et al., 2011): Character 1 is the component identifier with the pattern, which are Composite variables = X, Student = S, Parent = P, Mathematics teacher = M, Science teacher = N, and Administrator = A. Character 2 is the round identifier (i.e., 1, 2, 3), in which all base-year variables are "1" and subsequent rounds follow sequentially (e.g., first follow-up as "2," first update as "3," and so forth). Characters 3-12 indicate a descriptive name for the variable. Applying the patterns described above, let's take the variable S3FIELD_STEM as an example. The naming convention rules indicate that this should be a student variable, from the third wave of data collection, with the descriptor STEM field. This is fitting as this variable measured whether students were considering a major in a STEM field, and was collected during the update year.

Table 1. ***List of Variable Names***

Model Component	HSLS:09 Survey Item Description [Labels]	HSLS:09 Variable Name(s)
Endogenous Variables		
Selection of STEM major	What field of study or program will you be considering Whether respondent selected a STEM major 1 = yes and 0 = no	S3FIELD_STEM
Intent to pursue STEM career	What occupation do you expect to have at age 30 Whether respondent intend to have an occupation in the STEM field 1= yes and 0 = no	X2STU30OCC_STEM1
Mediating Variables		
Math and Science Self-Efficacy	You are confident that you can do an excellent job on tests in this course [S2MTESTS/ S2STESTS] You are certain that you can understand the most difficult material presented in the textbook used in this course [S2MTEXTBOOK/S2STEXTBOOK] You are certain that you can master the skills being taught in this course [S2MSKILLS/S2SSKILLS] You are confident that you can do an excellent job on assignments in this course [S2MASSEXCL/S2SASSEXCL] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	X2MTHEFF and X2SCIEFF

Math and Science Outcome Expectation	What students learn in this course is useful for everyday life [S2MUSELIFE/S2SUSELIFE] will be useful for college [S2MUSECLG/S2SUSECLG] will be useful for a future career [S2MUSEJOB/S2SUSEJOB] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	X2MTHUTI and X2SCIUTI
Math and Science Interest	You are enjoying this class very much [S2MENJOYING/S2SENJOYING] You think this class is a waste of your time [S2MWASTE/S2SWASTE] You think this class is boring [S2MBORING/S2SBORING] What is your favorite subject [S2FAVSUBJ] Rationale for students taking math/science course [S2MENJOYS/S2SENJOYS] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	X2MTHINT and X2SCIINT
Exogenous Variables		
Math Aptitude	Algebraic reasoning mathematics criterion-referenced assessment score	X2TXMSCR
Math and Science Identity	You see yourself as a math/science person [S2MPERSON1/S2SPERSON1] Others see you as a math/science person [S2MPERSON2/S2SPERSON2] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	X2MTHID and X2SCIID

STEM Informal Learning Participation	STEM informal learning participation within math clubs, math competitions, math summer programs, math study groups, math tutoring programs, science clubs, science competitions, science summer programs, or science study groups or science tutoring programs Scale score ranging from 0-5 for math and science each, measuring the number of different informal math or science activities students participated in	S2MCLUB, S2MCOMPETE, S2MSUMMERPRG, S2MGROUP S2MTUTORED, S2SCLUB, S2SCOMPETE, S2SSUMMERPRG, S2SGROUP, and S2STUTORED
Moderating Variables		
Math and Science Teacher Beliefs	The amount a student can learn is primarily related to family background [M1FAMILY/S1FAMILY] If students are not disciplined at home, they are not likely to accept any discipline at school [M1DISCIPLINE/S1DISCIPLINE] You are very limited in what you can achieve because a student's home environment is a large influence on their achievement [M1STUACHIEVE/S1STUACHIEVE] If parents would do more for their children, you could do more for your students [M1PARENT/S1PARENT] If a student did not remember information you gave in a previous lesson, you would know how to increase their retention in the next lesson [M1RETAIN/S1RETAIN]	X1TMEFF and X1TSEFF

	If a student in your class becomes disruptive and noisy, you feel assured that you know some techniques to redirect them quickly [M1REDIRECT/S1REDIRECT] If you really try hard, you can get through to even the most difficult or unmotivated students [M1GETTHRU/S1GETTHRU] When it comes right down to it, you really cannot do much because most of a student's motivation and performance depends on their home environment [M1HOMEFX/S1HOMEFX] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	
Math and Science Teacher Expectation	High school math/science teachers at your school set high standards for teaching [M1TEACHING/S1TEACHING] set high standards for students' learning [M1LEARNING/S1LEARNING] believe all students can do well [M1BELIEVE/S1BELIEVE] make expectations for instructional goals clear to students [M1CLEARGOALS/S1CLEARGOALS] have given up on some students [M1GIVEUP/S1GIVEUP] care only about smart students [M1CARE/S1CARE] expect very little from students [M1EXPECT/S1EXPECT] work hard to make sure all students are learning [M1WORKHARD/S1WORKHARD] 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, and 4 = *strongly agree*	X1TMEXP and X1TSEXP
Informal STEM exposure	Hold school-wide math or science fairs, workshops, or competitions Partner with community colleges or universities that offer math or science summer programs or camps for high school students	A1MTHSCIFAIR, A1MSSUMMER, A1MSAFTERSCH,

Sponsor a math or science after-school program Pair students with mentors in math or science Bring in guest speakers to talk to students about math or science Take students on math- or science-relevant field trips such as to a city aquarium or planetarium Tell students about regional or state math or science contests, math or science web sites and blogs, or other math or science programs online or in your community, such as a 21st Century Community Learning Center program Require teacher professional development in how students learn math or science Require teacher professional development in increasing student interest in math or science Something else Scale score ranging from 0-10, measuring the number of different forms of informal STEM exposure schools implement	A1MSMENTOR, A1MSSPEAKER, A1MSFLDTRIP, A1MSPRGMS, A1MSPDLEARN, A1MSPDINTRST, and A1MSOTHER

Analysis

Descriptive Analysis

Descriptive statistical analyses were conducted to gain insight into characteristics of the study's population. Initially, descriptions of the student population as a whole were composed, then disaggregation was engaged based on personal inputs relating to gender, race/ethnicity, and class. Components of STEM career development were disaggregated by sample sub-populations to identify potential trends and/or variations that might have existed with regard to student profile types. Special attention was paid to core model elements, i.e., STEM- self-efficacy, outcome expectation, and interests; intent to pursue STEM careers; and STEM major selection. Next, descriptive statistics were conducted on school-level variables, i.e., informal STEM exposure, teacher beliefs, and teacher expectations, to examine whether any themes might emerge. After variables were analyzed based on the school population as a collective, school-level analyses were disaggregated by school control type (i.e., public versus private), locale (i.e., rural, suburban, town, city) and geographical region (i.e., Northeast, West, South, Midwest). This provided more in-depth insight into potential differences that might exist in school structures based on environmental contexts. Together, these diverse profile types allowed for greater meaning making into how personal characteristics and environmental contexts might have shape, or otherwise been related to, students' STEM career development.

Structural Equation Modeling

Following descriptive statistics, the proposed STEM career development conceptual model was tested using structural equation modeling. A composite structural model was created, which included variables from three waves of data collection (2009 base year, 2012 follow-up, and 2013 update). Figure 5 below is a depiction of the composite structural model based on the conceptual model and longitudinal data.

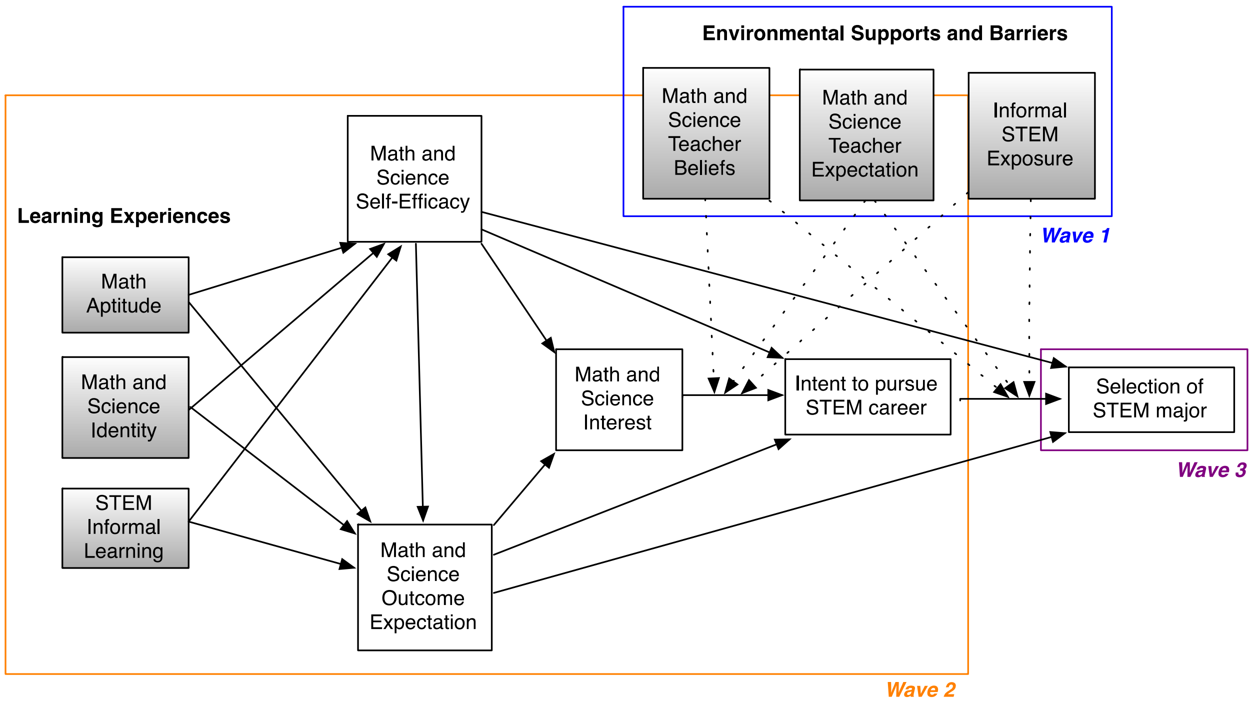


Figure 5. *STEM Career Development Composite Structural Model*
Note: The exogenous variables are shaded; all others are endogenous. Please also note that certain endogenous variables, namely math and science self-efficacy, math and science outcome expectation, math and science interest, and STEM career intent, are both independent and dependent variables, and thus mediate relationships. In addition, variables characterized as environmental supports and barriers function as moderators. Finally, the colored boxes indicate which wave of data variables were collected within.

The math-specific model (i.e., only math-related constructs) was postulated by five simultaneously estimated regression equations. The first equation investigated how math aptitude, math identity, and math informal learning influenced math self-efficacy. The second equation examined how math outcome-expectation was influenced by math aptitude, math identity, math informal learning, and math self-efficacy. The third equation examined how math self-efficacy and math outcome-expectation affected math interest. The fourth equation examined how intent to pursue a STEM career was affected by math self-efficacy, math outcome expectation, math interest, and environmental contexts (e.g., math teacher beliefs, math teacher expectations, and informal STEM exposure). The final equation examined how STEM major selection was influenced by math self-efficacy, math outcome expectation, intent to select STEM career, and environmental contexts. A second model, including only science-related constructs, was postulated afterwards.

Structural equation modeling analyses were conducted using WarpPLS 5.0, a structural equation modeling (SEM) statistical software that employs the partial least square (PLS) method (Kock, 2015). More specifically, WarpPLS was used during analyses of the larger contextual model, which included core SCCT model elements (i.e., self-efficacy, outcome expectation, and interest) as well as students' learning experiences and teacher and school environmental factors. Rationale for utilization of WarpPLS rested in the fact that it allowed for the calculation of moderating effects, which was essential to the proposed model.

Given that my outcome variables were dichotomous, as indicated in regression equations 4 and 5 above, the Robust Path Analysis algorithm was used for the outer model. Further, the Warp 3 algorithm was utilized for the inner model analyses, which calculated the "S shaped" relationship between the independent and dependent variables. Goodness of fit assessed seven model fit and quality indices. These included Average block VIF (AVIF); Average full collinearity VIF (AFVIF); Tenenhaus GoF (GoF); Sympson's paradox ratio (SPR); Statistical suppression ratio (SSR); and Nonlinear bivariate causality direction ratio (NLBCDR) . The following guidelines were used to assess model quality and fit (Kock, 2015):

AVIF: acceptable if <= 5, ideally <= 3.3

AFVIF: acceptable if <= 5, ideally <= 3.3

GoF: small >= 0.1, medium >= 0.25, large >= 0.36

SPR: acceptable if >= 0.7, ideally = 1

RSCR: acceptable if >= 0.9, ideally = 1

SSR: acceptable if >= 0.7

Data used in analyses conducted using WarpPLS were automatically standardized during the data processing procedure, as such, all results reported reflect standardized estimates.

Multiple-Group Analysis

It was essential to identify potential differences that might have existed in students' STEM career development process based on personal characteristics like race/ethnicity, gender, and socio-economic status. Therefore, after the full sample structural equation modeling analysis was conducted, analyses by subpopulation followed. Between-group comparisons using the math-specific core SCCT model, which only included self-efficacy, outcome expectation, and interest as predictors of intent to select a STEM career and selection of a STEM major, were engaged. Three sets of analyses were conducted, namely by race/ethnicity, which compared White, Asian, Black, and Latino subpopulations; gender, which compared males and females; and socio-economic status, which compared socio-economic quintiles. This analysis examined whether there were significant differences in the model's structural patterns.

Multi-group analyses were conducted using MPlus 7.4, a statistical modeling software that allows for the analysis of clustered, multi-level data (Muthén & Muthén, 1998-2015). It also permits the use of analytical weights during the analysis process. These capabilities were important given the complex structure of HSLS:09 data. Mplus allowed for the use of a mixture of variable types (Muthén & Muthén, 1998-2015), thus accommodating both continuous and categorical data.

The model was estimated using the weighted least squares means and variance (WLSMV) method. This method allows for robust estimations using categorical data, which was important given the nature of my outcome variables. The theta parameterization method was used to accommodate the inclusion of a categorical predictor (i.e., STEM career intentions) and outcome variable (i.e., STEM major selection) in my model. Overall model goodness of fit was tested using Comparative Fit Index (CFI), Tucker-Lewis Fit Index (TLI), root mean square error of approximation (RMSEA), and Chi-square indices. Chi-square is not a good index alone (Brown, 2006), thus this study reported the ratio of Chi-square and degrees freedom, which provides a better indication of model quality. The following guidelines were used to assess model quality and fit: CFI values close to or greater than 0.95; TFI values close to or greater than 0.95; and RMSEA values close to or below 0.05 (Brown, 2006). Additionally, values less than 3.84 were used to assess the ratio of Chi-square and degrees freedom.

Intersectional Perspective

Findings gained primarily from descriptive statics, with supplements from structural equation modeling analyses, were used to gain an intersectional understanding of STEM career development. These analyses not only provided insight into racial, gendered, and class categories separately, they also allowed for meaning making when considering the overlap of students' identities. Further, discussions were engaged regarding how the intersection of these characteristics (i.e., race, class, gender) coupled with career development constructs (e.g., self-efficacy, outcome expectation, interest, etc.) operates within the context of larger systems.

Missing Data

Missing data can greatly affect the results of analytics conducted, as most statistical software exclude records with incomplete information. As a result, the utility of data is lessened.

While there was not a high level of item non-response, HSLS:09 identified key variables for item imputation to aid in the facilitation of complete-case analyses. To account for potential issues that may arise due to missing data, most variables utilized within this study were those that have been imputed, instead of those originally included within questionnaire instrumentation. The advantage of using such values is that it allowed for the use of all respondent records during analysis. Subsequently, more power for statistical tests was afforded.

To address potentially missing data that resulted after these precautions had been taken, particular actions were taken within Mplus and WarpPLS accordingly. Within MPlus, the WLMSV estimation method handled the missingness by allowing it to be a function of the observed covariates but not the observed outcomes (i.e., missing at random assumption, Muthén & Muthén, 1998-2015). More specifically, when TYPE=MISSING; with the WLMSV estimator was used, a pairwise present method was used when there were no covariates in the model (Asparouhov & Muthén, 2010; Muthén & Muthén, 1998-2015). When there were covariates, however, missingness was a function of the observed covariates (Muthén & Muthén, 1998-2015) Within WarpPLS, the Arithmetic Mean Imputation missing data imputation algorithm was used, which replaced missingness with column averages (Kock, 2015).

Chapter 4: Findings

This purpose of this research was to understand high school students' STEM career development. Assumptions core to Social Cognitive Career Theory, structural equation modeling techniques, and intersectional approaches were used to gain insight into this complex phenomenon. This chapter will present all research findings that were derived after implementing those approaches. Chapter four begins by reporting students' demographic information, including an intersectional analysis of identity categories. Descriptive findings regarding students' learning experiences and schools' environmental supports and barriers will follow. Finally, findings by research questions are presented. As the purpose of Chapter four is to present research findings, a detailed discussion of results will be engaged in Chapter five.

Descriptive Statistics

General Descriptive Statistics

About 52 percent of the student population identified as White, 14 percent Black, 22 percent Latino, and 3.5 percent Asian. Additionally, about nine percent of students identified as American Indian, Pacific Islander, or mixed race. Within this research's analyses, when speaking of the student population overall, all races/ethnicities will be included. Otherwise, during analyses examining potential racial/ethnic subgroup differences, only White, Black, Latino, and Asian subpopulations will be observed. With regard to gender, male students made up 50.3 percent of the population. Finally, about 24 percent of students were within the lowest socio-economic quintile and 23 in the highest. Table 2 illustrates students' demographic information in each of these identity categories.

Table 2. ***Student Demographics***

Population Race	N	%
American Indian/Alaskan Native, non-Hispanic	28,875	0.7
Asian, non-Hispanic	147,067	3.5
Black/African American, non-Hispanic	569,991	13.7
Latino, no race specified	62,572	1.5
Latino, race specified	866,056	20.8
More than one race, non-Latino	310,618	7.5
Native Hawaiian/Pacific Islander, non-Hispanic	19,002	0.5
White, non-Hispanic	215,1495	51.8

Table 2. ***Student Demographics***

	N	%
Population Race		
Racial Subgroups		
Asian	147,067	3.5
Black	569,991	15.0
Latino	928,628	24.5
White	2,151,495	56.7
Gender		
Male	2,088,375	50.3
Female	2,067,302	49.7
Socio-economic Quintiles		
Lowest quintile	994,458	24.1
Second quintile	719,350	17.4
Third quintile	700,416	17.0
Fourth quintile	760,889	18.5
Highest quintile	947,785	23.0

*Race and gender weighted by W2Student
*Socio-economic quintiles weighted by W2Parent
**Latino consists of Latino students who both specified and did not specify race

Intersectional Descriptive Statistics

When intersectional analyses are reported throughout this research, both within- (column%) and between- (row%) group statics will be presented. Within-group statics provide insight regarding descriptive information of a specific group's (e.g., male, White, or lowest socio-economic quintile) distribution on a given variable. Between-group statistics provide insight regarding descriptive information between all sub-groups within a particular population comparatively (e.g., comparison of White, Black, Asian, and Latino within race/ethnicity), thus indicates the percentage of distribution each sub-group represents within the respective population on a given variable (i.e., between-group/row% will amount to 100 percent when all sub-group percentages are added together). Both group analysis types are included because they provide different forms of information (i.e., regarding sub-groups independently and sub-groups comparatively), which then allows for multiple levels of interpretation.

Race/ethnicity and Socio-economic Status

Considering the intersection among identity categories, Whites overwhelmingly comprise the highest socio-economic quintile (75 percent), while Latinos most represent those in the lowest quintile (44 percent). Further, as indicated in Table 3 below, Whites and Asians are highest represented in the highest quintile (30 and 39 percent, respectively). Conversely, Blacks and Latinos are highest represented in the lowest quintile (36 and 43 percent, respectively). Essentially, Whites and Asians are over-represented in the highest socio-economic quintile, while Blacks and Latinos are over-represented in the lowest. See table 3.

Table 3. ***Intersection between Race and Socio-economic Status***

	Socio-economic Status Quintiles Column % (Row %)				
Race	Lowest Quintile	Second Quintile	Third Quintile	Fourth Quintile	Highest Quintile
White	31.6 (13.3)	51.6 (15.7)	60.4 (18.3)	69.2 (22.3)	75.4 (30.4)
Black	22.5 (36.1)	15.8 (18.3)	16.7 (19.4)	10.5 (12.8)	8.7 (13.4)
Latino	43.5 (42.9)	30.3 (21.6)	19.4 (13.8)	16.8 (12.7)	9.6 (9.1)
Asian	2.4 (15.8)	2.3 (10.8)	3.5 (16.5)	3.6 (17.7)	6.3 (39.2)

*Weighted by W2Parent

<u>Gender and Socio-economic Status</u>

There is an equal distribution of male and female students within each quintile. Overall, the percentile distribution of gender intersected with socio-economic status mirrors that of the population's overall gender and socio-economic distributions. See table 4.

Table 4. ***Intersection between Gender and Socio-economic Status***

	Socio-economic status quintiles Column % (Row %)				
Gender	Lowest Quintile	Second Quintile	Third Quintile	Fourth Quintile	Highest Quintile
Male	49.8 (23.9)	50.5 (17.5)	50.5 (17.1)	48.7 (17.9)	51.3 (23.5)
Female	50.2 (24.3)	49.5 (17.3)	49.5 (16.9)	51.3 (19.0)	48.7 (22.5)

*Weighted by W2Parent

Race and Gender

With the exception of gender within the Black student subpopulation, where female students are slightly more represented (54 percent) than male students (46 percent), race and gender distributions are consistent with that of the larger student population. See table 5.

Table 5. ***Intersection between race and gender***

	Gender Column % (Row %)	
Race	Male	Female
White	57.9 (51.4)	55.4 (48.6)
Black	13.7 (46.0)	16.3 (54.0)
Latino	24.5 (50.5)	24.4 (49.5)
Asian	3.8 (49.5)	3.9 (50.5)

*Weighted by W2Student

Race, Gender, and Socio-economic Status

Finally, when considering the overlap among race, socio-economic status, and gender, similar trends as those discussed above continue to emerge. Blacks and Latinos are over-represented in the lowest socio-economic quintile, while being under-represented in the highest quintile. The reverse holds true for Asians and Whites. In addition, overwhelmingly, Latino males and females are the highest represented in the lowest quintile (46.9 and 40.2 percent, respectively). Table 6 presents the intersection among students' diverse identity characteristics.

Table 6. ***Intersection among Race, Socio-economic Status, and Gender***

	Socio-economic Status Intersected with Gender Column % (Row %)									
	Lowest Quintile		Second Quintile		Third Quintile		Fourth Quintile		Highest Quintile	
Race	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
White	32.2 (49.8)	31.1 (50.2)	50.7 (50.0)	52.5 (50.0)	63.6 (53.3)	57.0 (46.7)	70.7 (49.4)	67.8 (50.6)	78.2 (52.3)	72.7 (47.7)
Black	18.2 (39.7)	26.5 (60.3)	15.1 (48.6)	16.5 (51.4)	14.1 (42.7)	19.3 (57.3)	9.6 (44.3)	11.3 (55.7)	7.1 (41.4)	10.3 (58.6)
Latino	46.9 (52.8)	40.2 (47.2)	31.6 (53.0)	29.0 (47.0)	17.8 (46.5)	21.0 (53.5)	16.6 (47.8)	16.9 (52.2)	9.3 (49.1)	9.8 (50.9)
Asian	2.7 (54.0)	2.2 (46.0)	2.6 (57.0)	2.0 (43.0)	4.4 (63.2)	2.6 (36.8)	3.1 (42.6)	4.0 (57.4)	5.4 (43.1)	7.2 (56.9)

*Weighted by W2Parent
Note: Row percentages are within each quintile, respectively.

Learning Experiences

Math Aptitude

Overall, the mean of students' math aptitude score was 64.38, with a standard deviation of 19.00. Male and female students' aptitudes were nearly identical, with male students having slightly higher mean scores. Asian students had the highest mean score (79.09), while Black students had the lowest mean score (55.41). Students' scores increased with socio-economic status, with the lowest quintile having a mean score of 55.95 and the highest with 76.12. Table 7a below provides descriptive statistics of students' math aptitude by gender, race/ethnicity, and socio-economic status.

Table 7a. ***Students' Math Aptitude***

Subgroup Group	M	SD
All	64.38	19.00
Gender		
Male	64.45	19.62
Female	64.31	18.35
Race/Ethnicity		
White	67.67	18.93
Asian	79.09	19.39
Black	55.41	16.23
Latino	60.33	17.45
Socio-Economic Status		
Lowest quintile	55.95	16.67
2nd quintile	60.13	17.54
3rd quintile	62.00	17.44
4th quintile	67.55	18.27
Highest quintile	76.12	18.40

*All, gender, and race/ethnicity Weighted by W2Student.
Socio-economic status weighted by W2Parent

When considering the intersection among diverse identity categories, in each quintile, Asian students had higher mean scores than their male and female counterparts across race. Additionally, though male students had higher mean scores than female students when comparing gender only, female Asian students outperformed all other within-quintile groups. The exceptions were scoring nearly identical to male Asian students in the fourth quintile, and scoring less than male Asian students in the third quintile. Conversely, Black students had lower mean scores than all other groups. Again, despite male mean scores being higher than female mean scores overall, Black female students outperformed Black male students in each quintile, except the third quintile. The same anomaly holds true for Latino and White students; all female students had higher mean scores than their male counterparts, with the exception of those in the third quintile. The lowest scoring group overall was Black male students in the lowest quintile, with an average score of 49.2. The highest performing group was male Asian students in the third quintile, with an average score of 86.9. Table 7b below provides descriptive statistics of students' math aptitude with the intersection among race/ethnicity, gender, and socio-economic status.

Table 7b. ***Students' Math Aptitude with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender																			
	Lowest quintile				Second quintile				Third quintile				Fourth quintile				Highest quintile			
	Male		Female		Male		Female		Male		Female		Male		Female		Male		Female	
Racial Subgroup	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
White	57.9	18.1	61.2	18.8	63.7	18.4	69.5	18.7	77.5	18.5	55.3	16.7	62.4	16.6	64.4	16.3	69.5	17.1	76.7	16.4
Asian	68.0	16.9	75.0	20.0	77.3	18.7	81.3	17.7	86.9	19.4	71.3	18.7	69.7	19.8	69.6	16.4	80.6	18.4	86.7	16.5
Black	49.2	13.4	51.9	16.1	53.1	15.0	59.3	17.1	62.1	18.6	51.6	14.0	55.5	15.7	57.3	15.6	58.7	15.3	71.5	15.2
Latino	57.7	16.1	61.1	16.5	60.2	17.9	64.0	17.2	67.9	20.0	56.6	16.2	59.2	17.3	60.5	16.5	63.1	19.3	72.5	18.5

*Weighted by W2Parent

Math and Science Identity

Math and science identity composite scores were standardized to a mean of 0 and a standard deviation of 1. The mean value of math identity was -0.0025, with a standard deviation of 0.9998. To test to see if similarity in mean and standard deviation was due to sample size, I randomly sampled ten percent of all cases. While there was slightly more variation, the means were still very close to zero (M = 0.255) and standard deviations were almost identical to 1 (SD = 1.0093). With regard to science identity, the mean was 0.0022, with a standard deviation of 1.0000. When analyzing a random sample of 10 percent of all cases, the mean of science identity returned to be .0064, with a standard deviation of 1.0353. Skewness of both components were nearly zero, implying normal distribution.

Math identity increased with socio-economic status. Students in the lowest socio-economic quintile had the lowest math identity (M = -0.06) while students in the highest socio-economic quintile had the highest (M = 0.20). Male (M = 0.08) and female math identity (M = -0.09) also differed. Finally, with regard to race, Asians had the highest math identity (M = 0.39) followed by Blacks (M = 0.02), Whites (M = 0.00), and Latinos (M = -0.07).

Science identity increased with socio-economic status. Students in the lowest socio-economic quintile had the lowest science identity (M = -0.16) while students in the highest socio-economic quintile had the highest (M = 0.26). Male (M = 0.04) and female science identity (M = -0.04) also differed. Finally, with regard to race, Asians had the highest science identity (M = 0.17) followed by Whites (M = 0.06), Blacks (M = -0.07), and Latinos (M = -0.13).

When testing to see if there were significant differences in math- and science-identity, based on race/ethnicity, gender, or socio-economic status, each test returned significance with p values less than .001.

Math and Science Informal Learning Experiences

Only 26 percent of students participated in a math-related informal learning experience. Seventeen percent of students participated in at least one math-related informal learning experience, about six percent participated in two, and less than three percent of students participated in three or more. The math-related informal experiences that were most engaged by students were math tutoring programs (17.1 percent) and math study groups (10.2 percent). In contrast, students were least likely to participate in math clubs, summer programs, or competitions (3.3, 3.8, and 4.6 percent respectively).

Students were even less likely to participate in informal science learning experiences, where 82 percent of students reported never participating in any science-related informal learning experiences. Eleven percent of students participated in one science-related activity, four percent participated in two, and 2.4 percent participated in three or more activities. Science study groups (8 percent) and science tutoring programs (6.8 percent) were most engaged by students. In contrast, science competitions, clubs, and summer programs (5.4, 5.1, and 3.3 percent, respectively) were participated in least by students. Table 8 provides statistics regarding the percentage of students participating in each type of math and science informal learning activity. Additionally, Table 9 outlines the number of informal learning activity types participated in by students.

Table 8. ***Descriptive Statistics of Informal STEM Participation***

	Informal Learning Type	
	Math	Science
Informal Learning Activity	%	%
Club	3.6	5.1
Competition	4.6	5.4
Program	3.8	3.3

Table 8. ***Descriptive Statistics of Informal STEM Participation***

Study group	10.2	8
Tutoring	17.1	6.8

Table 9. ***Overall Math and Science Informal Learning Participation***

	Informal Learning Type	
	Math Informal Learning	Science Informal Learning
Number of Informal Learning Experience Types	%	%
Zero	73.9	82
One	17	11.3
Two	6.2	4.4
Three	1.9	1.4
Four	0.6	0.5
Five	0.4	0.4

Math and Science Informal Learning Participation by Race

When analyzing informal learning participation by race, Asian students participated in the most informal learning math experiences, while White students participated in the least amount of math activities. More than 22 percent of Black students participated in at least one math activity, followed by Asian, Latino, and White students. More than 22 percent of Asian students participated two or more math activities, nearly double or more than that of students in other racial/ethnic groups. Across all races, math tutoring programs were most engaged, followed by math study groups. Blacks and Latinos were least likely to participate in math competitions, while White students were least likely to participate in math summer programs.

Overall, students participated in more math informal learning experiences than science. Again, Asian students participated in science informal learning experiences at higher percentages than all other racial/ethnic groups, while White students participated at the lowest rate. Nearly 20 percent of Asian students participated in at least two science activities, more than double that of

Black students, more than triple that of Latino students, and almost quadruple that of White students. Science study groups were participated in most by Asian, White, and Black students, while Latino students engaged in tutoring programs slightly more. Science summer programs were participated in least by all students, except Blacks, who were least likely to participate in science clubs. Table 10 below provides descriptive information on informal learning participation by racial/ethnic group. Additionally, Table 11 outlines the number of different informal learning activity types participated in by students.

Table 10. ***Descriptive Statistics of Informal STEM Participation by Race***

	Race			
	White %	Black %	Latino %	Asian %
Math Informal Learning Activity				
Math club	3.1	3.6	3.5	11.8
Math competition	5	3.5	3.1	12.3
Math summer program	1.7	6.8	5.2	11.8
Math study group	8.1	14.6	10.6	21
Tutored in math	13.7	24.6	18.2	24.3
Science Informal Learning Activity				
Science club	5.1	4.1	4.3	14.3
Science competition	5.3	5.6	4.5	12.7
Science summer program	2.2	5	3.3	10
Science study group	6.8	9.7	8.6	17.3
Tutored in science	4.7	9.6	8.7	11.8

Table 11. ***Frequency of Informal Learning Participation by Race***

	Race			
	White %	Black %	Latino %	Asian %
Math Informal Learning Participation				
Zero Activities	77.5	66	73.8	56.7
One Activity	15.7	22.1	16.4	21
Two Activities	5.2	7.3	7	11.3
Three Activities	1.3	2.9	1.5	7.1
Four Activities	0.2	1.1	0.8	2.3

Table 11. ***Frequency of Informal Learning Participation by Race***

	Race			
	White %	Black %	Latino %	Asian %
Five Activities	0.2	0.5	0.5	1.6
Science Informal Learning Participation				
Zero Activities	83.5	80.4	82.2	65.5
One Activity	11	10.6	11.5	15.3
Two Activities	3.9	6	3.8	11.1
Three Activities	1.1	1.4	1.4	4.7
Four Activities	0.3	1.2	0.3	2

Math and Science Informal Learning Participation by Gender

There was little difference of participation by gender, though female students participated in informal math and science learning experiences at slightly higher rates. Across gender, students participated in more math experiences than science. About 23 percent of male students participated in math informal learning activities and nearly 30 percent of female students participated in math informal experiences. Only about 16 percent of male students participated in science experiences whereas slightly less than 20 percent of female students participated similarly. Overall, math tutoring programs were most engaged, while math clubs were participated in least. With regard to science, study groups were most engaged, while science summer programs were participated in least. Tables 12 and 13 below provide an overview of math and science informal learning participation by gender.

Table 12. ***Descriptive Statistics of Informal STEM Participation by Gender***

	Gender	
	Male %	Female %
Math Informal Learning Activity		
Math club	3.5	3.8

Table 12. ***Descriptive Statistics of Informal STEM Participation by Gender***

	Gender	
	Male	Female
	%	%
Math competition	5	4.1
Math summer program	3.6	4
Math study group	7.7	12.6
Tutored in math	14.6	19.6
Science Informal Learning Activity		
Science club	4.8	5.4
Science competition	6.1	4.8
Science summer program	3.1	3.5
Science study group	6.9	9.1
Tutored in science	6	7.6

Table 13. ***Frequency of Informal Learning Participation by Gender***

	Gender	
	Male	Female
	%	%
Math Informal Learning Participation		
Zero Activities	77.2	70.6
One Activity	15.4	18.6
Two Activities	4.5	8
Three Activities	1.8	2
Four Activities	0.6	0.5
Five Activities	0.5	0.3
Science Informal Learning Participation		
Zero Activities	83.7	80.2
One Activity	10.1	12.4
Two Activities	3.5	5.3
Three Activities	1.6	1.3
Four Activities	0.5	0.5
Five Activities	0.5	0.3

Math and Science Informal Learning Participation by Socio-economic Status

Examining informal STEM participation by socio-economic status, students participated in math and science tutoring most. Conversely, math and science summer programs and clubs were typically least engaged. Student in the highest socio-economic quintiles participated in all informal learning activities at higher percentages than all other quintiles, with the exception of math summer programs, which were participated in most by students in the lowest socio-economic quintile.

Students in the highest socio-economic quintile had the largest percentage of students within their group to participate in informal STEM learning, with nearly 35 percent participating in at least one math activity and nearly 28 percent in a science activity. Students in the lowest socio-economic group were second highest in terms of participation in informal STEM learning. Interestingly, students in the fourth quintile participated in STEM informal learning at the lowest frequency, where only 27 percent participated in at least one math activity and 19 percent in at least one science activity. Tables 14 and 15 below provide information regarding students' informal math and science participation by socio-economic status.

Table 14. ***Descriptive Statistics of Informal STEM Participation by Socio-economic Status***

	Socio-economic Quintile				
	Lowest %	2nd %	3rd %	4th %	Highest %
Math Informal Learning Activity					
Math club	2.6	4.2	2.9	4.5	6.3
Math competition	2.7	3.9	3.9	5.5	8.2
Math summer program	5.8	3.9	3.7	3.8	4.5
Math study group	7.7	10.8	10.5	9.5	14.4
Tutored in math	15.1	17.1	15.8	17.7	19.8
Science Informal Learning Activity					
Science club	3.4	5.1	4.7	6.6	8
Science competition	4.1	6.3	4.3	5.9	9.4

Table 14. ***Descriptive Statistics of Informal STEM Participation by Socio-economic Status***

	Socio-economic Quintile				
	Lowest	2nd	3rd	4th	Highest
	%	%	%	%	%
Science summer program	3.0	3.2	2.4	4.2	6.3
Science study group	7.8	6.4	8.4	8.2	12.5
Tutored in science	6.9	7.9	5.6	5.8	8.0

Table 15. ***Frequency of Informal Learning Participation by Socio-economic Status***

	Socio-economic Quintile				
	Lowest	2nd	3rd	4th	Highest
	%	%	%	%	%
Math Informal Learning Participation					
Zero Activities	78.1	75.2	75.9	72.7	65.9
One Activity	14.0	13.9	15.7	17.1	21.2
Two Activities	5.0	8.1	5.7	7.4	8.5
Three Activities	1.8	1.9	1.4	2.3	3.3
Four Activities	0.6	0.5	0.6	0.3	0.6
Five Activities	0.4	0.4	0.7	0.2	0.5
Science Informal Learning Participation					
Zero Activities	85	82	84	80.5	72.5
One Activity	9.7	11	10.5	12.3	16.5
Two Activities	3.2	4.7	3.2	4.4	7.3
Three Activities	0.9	1.3	1.5	1.8	2.5
Four Activities	0.4	0.4	0.1	0.8	0.7
Five Activities	0.7	0.6	0.7	0.3	0.6

Environmental Supports and Barriers

School Descriptive Statistics

Nearly 93 percent of schools included in the study were public while seven percent were private. Additionally, nearly 32 percent of schools were located in the city, 33.3 percent in the suburbs, 11.7 percent in a town, and 23.1 percent in a rural location. Finally, 17.3 percent of schools were located in the Northeast, 22.2 in the Midwest, 37.6 in the South, and 22.9 in the West.

School Informal STEM Exposure

More than 98 percent of schools reported that they provided informal STEM exposure to their students and staff on some level. Telling students about regional or state math or science contests, math or science web sites and blogs, or other math or science programs online or in the community was most engaged, where more than 68 percent of schools participated in this activity. Similarly, school were also likely to take students on math- or science-relevant field trips (64.3 percent); bring in guest speakers to talk to students about math or science (60.7 percent); require teacher professional development in how students learn math or science (58.8 percent); and sponsor a math or science after-school program (54.8 percent). Conversely, pairing students with mentors in math or science was least engaged, where less than 37 percent of schools reported offering this type of exposure. Similarly, schools were least likely to hold school-wide math or science fairs, workshops, or competitions (39.3 percent); require teacher professional development in increasing student interest in math or science (40.1 percent); or partner with community colleges or universities that offer math or science summer programs or camps for high school students (46.8 percent).

School Type

Examining informal STEM exposure by school type, public schools engaged in more activities promoting STEM exposure than private schools, with the exceptions of taking students on field trips and telling students about programs available online or in the community. Public schools were most likely to tell students about math or science programs online or in their community (67.8 percent) and least likely to pair students with math or science mentors (37 percent). Private schools were most like to take students on field trips (67.7 percent) and least likely to require teacher professional development to increase student interest in math or science (27.8 percent).

School Locale

There were not substantial differences in informal STEM exposure when examining by school locale. Rural schools provided the least exposure to their students in nearly every activity type, while suburban schools provided the most exposure in most activity types. Looking within each school locale, city and suburban schools were most likely to tell students about math or science programs online or in their community (71.4 and 75.2 percent, respectively). City schools were least likely to require teacher professional development to build student interest in math and science. Suburban schools were least likely to pair students with mentors. Town schools were most likely to bring guests in to talk to students about math or science (63.8 percent) and least likely to hold school-wide math or science fairs, workshops, or competitions (32 percent). Rural schools were most likely to take students on math- or science-relevant field trips (64.3) and least likely to pair students with mentors (28.1).

Geographical Location

Finally, when considering schools' geographical region, the South and Northeast provided STEM exposure at the highest percentages. When examining within group distributions, nearly three-quarter of schools in the Northeast were most inclined to take their students on field trip, but most were least inclined to require teacher professional development to build students' interest in math or science (29.9 percent). Within the Midwest, schools most often exposed students to math or science programs online or in their community (67.6 percent), but paired students with mentors least (31.3 percent). More than three-fourths of schools in the South require teacher professional development in how students learn math or science, while pairing students with mentors was least engaged (39.5). Finally, within the West, schools most often took students on field trips (58.6 percent) and least often required teacher professional development to build student interest in math and science (31.3 percent). Table 16 below provides information regarding schools' informal STEM exposure by school type, locale, and geographical region. Additionally, Tables 17a-d include the intersection among these three school categories.

Table 16. ***School Informal STEM Exposure***

		School Type		School Locale				School Geographical Region			
Informal STEM Exposure Activity	All %	Public %	Private %	City %	Suburb %	Town %	Rural %	Northeast %	Midwest %	South %	West %
Holds math or science fairs/workshops/competitions	39.3	39.8	33.4	39.5	46.4	32	32.5	33.4	31.4	49.9	34.7
Partners w/ college/university that offers math/science summer program	46.8	47.5	36.4	50.5	45.6	54.4	39.1	62.8	39.9	49	37.4
Sponsors a math or science after-school program	54.8	55.7	43.2	60.5	57.4	54.3	43.3	57.6	44.9	61.6	51.4
Pairs students with mentors in math or science	36.8	37	34.9	40	37.7	42.4	28.1	31.7	31.3	39.5	41.9
Brings in guest speakers to talk about math or science	60.7	60.9	58.2	57.7	63.4	63.8	59.2	62.5	54.7	66.6	55.6
Takes students on math- or science-relevant field trips	64.3	64	67.7	59.1	69.8	62.4	64.3	74.3	60.9	65	58.6
Tells students about math/science contests/websites/blogs/other programs	68.2	67.9	72.7	71.4	75.2	59.5	58.2	71.7	67.6	73.6	57.6
Requires teacher prof development in how students learn math/science	58.8	59.4	50.4	60.7	63.4	55.8	50.7	46.6	49.7	75.2	51
Requires teacher prof development in increasing interest in math/science	40.1	41	27.8	37.4	43.2	42.8	37.8	29.9	40.4	50.4	31.3

Table 17a. ***School Informal STEM Exposure Northeast Intersection***

	Northeast							
	City		Suburb		Town		Rural	
Informal Learning Exposure	Public %	Private %	Public %	Private %	Public %	Private %	Public %	Private %
Holds math or science fairs/workshops/competitions	6.2	45	48.1	41.5	48.9	68.8	33.9	34.3
Partners w/ college/university that offers math/science summer program	82.9	45.3	61	9.3	78.6	37.1	52	63.7
Sponsors a math or science after-school program	66.1	58.7	60	52.4	43.5	0	44.5	100
Pairs students with mentors in math or science	27.6	57.9	34	36.2	63.2	21.7	14.1	36.3
Brings in guest speakers to talk about math or science	57	58.8	64.8	69.5	55.9	22.1	69.5	34.3
Takes students on math- or science-relevant field trips	68.1	49.4	73.5	68.7	97.3	68.8	83.8	70.6
Tells students about math/science contests/websites/blogs/other programs	68.7	80.1	79.7	68.5	60.5	59.3	63.7	63.7
Requires teacher prof development in how students learn math/science	37.2	82.7	58.2	30.6	54.6	37.1	36.8	0
Requires teacher prof development in increasing interest in math/science	18.9	30.3	45.6	28.2	18	25	20	0
Raises students' interest/achievement in another way	72.1	19.8	28	16.7	47.3	22.1	36.2	0

Table 17b. ***School Informal STEM Exposure Midwest Intersection***

	Midwest							
	City		Suburb		Town		Rural	
Informal Learning Exposure	Public %	Private %	Public %	Private %	Public %	Private %	Public %	Private %
Holds math or science fairs/workshops/competitions	48.2	23	25.8	14.1	24.7	11.3	29.1	40.7
Partners w/ college/university that offers math/science summer program	48.3	41.7	37.1	49.7	51.2	64	26.5	27.6
Sponsors a math or science after-school program	80.1	26.3	48.7	57.4	36.2	46.1	15.4	36.5
Pairs students with mentors in math or science	44.3	31.4	35.7	20.5	19.9	46.1	21.2	43.9
Brings in guest speakers to talk about math or science	61.1	45.5	46.3	65	68.2	13.6	51.4	43.9
Takes students on math- or science-relevant field trips	60	57.6	59.2	63.4	61.8	42.6	67.7	11.6
Tells students about math/science contests/websites/blogs/other programs	76.4	89.1	75.9	99.1	60.8	100	52	16.3
Requires teacher prof development in how students learn math/science	67.9	24.5	47.9	43.5	62.4	0	26.1	100
Requires teacher prof development in increasing interest in math/science	57.7	22.6	43.8	33.2	48.3	0	18.1	36.5
Raises students' interest/achievement in another way	22.8	22.3	24.2	14.7	25.6	0	26.6	20.2

Table 17c. ***School Informal STEM Exposure South Intersection***

	South							
	City		Suburb		Town		Rural	
Informal Learning Exposure	Public %	Private %	Public %	Private %	Public %	Private %	Public %	Private %
Holds math or science fairs/workshops/competitions	51.7	35.6	64.5	59.9	38.2	52.1	39.5	50.5
Partners w/ college/university that offers math/science summer program	62.6	36.9	40.2	49.1	45.5	45.1	48.8	84.9
Sponsors a math or science after-school program	72.8	43.7	62.2	33.1	67.9	24.4	53.5	35.4
Pairs students with mentors in math or science	40.4	43.6	45.1	37.8	44.6	8.5	31.3	0
Brings in guest speakers to talk about math or science	74.4	50.9	74	66.4	61.2	58	56.3	100
Takes students on math- or science-relevant field trips	66.7	72.4	71.8	92.4	48.2	45	60.6	100
Tells students about math/science contests/websites/blogs/other programs	69.2	80	79.7	85.7	67.5	62.6	72.6	35.4
Requires teacher prof development in how students learn math/science	83.4	45.3	81.5	61.2	74.1	39.9	67.5	35.4
Requires teacher prof development in increasing interest in math/science	56.5	18.4	48	16	53.8	16.1	52.4	84.9
Raises students' interest/achievement in another way	39.1	18	31.1	24.2	36.7	38.9	16.9	0

Table 17d. ***School Informal STEM Exposure West Intersection***

	West							
	City		Suburb		Town		Rural	
Informal Learning Exposure	Public %	Private %	Public %	Private %	Public %	Private %	Public %	Private %
Holds math or science fairs/workshops/competitions	45.2	12.3	39.1	0	24.5	11.9	13.1	0
Partners w/ college/university that offers math/science summer program	24.8	51	54.2	18.2	63	0	15.9	0
Sponsors a math or science after-school program	41.1	49.4	59.7	18.2	68.4	0	53.2	0
Pairs students with mentors in math or science	44.2	29.5	34.4	0	64.6	0	39.9	0
Brings in guest speakers to talk about math or science	40.5	74.6	59.8	58.7	69.1	11.9	73.8	0
Takes students on math- or science-relevant field trips	42.6	85.6	70.5	100	70	88.1	59.3	0
Tells students about math/science contests/websites/blogs/other programs	68.2	80.8	64.3	18.2	44	21.4	23.4	0
Requires teacher prof development in how students learn math/science	50.7	75.9	60.8	100	23	0	45.1	0
Requires teacher prof development in increasing interest in math/science	22.8	29.9	36.2	100	33.3	0	38.5	0
Raises students' interest/achievement in another way	39.6	20.8	12.4	0	39.6	21.4	8.2	0

Teacher Beliefs and Expectations

When analyzing the descriptive statics of math and science teachers' beliefs and perceptions of expectations, the means all showed to be nearly zero with a standard deviation of nearly one. This was expected, as these variables were standardized. Next, analysis of skewness and kurtosis of each component was conducted. For math teacher beliefs, skewness yielded -0.252 and kutosis yielded 0.246. For math teacher perceptions of expectations, skewness yielded -0.750 and kurtosis yielded 0.731. For science teacher beliefs, skewness was -0.115 and kurtosis was 0.270. Science teacher perceptions of expectations yielded a skewness of -0.613 and kurtosis of 0.256. Skewness statistics implies that math and science teacher beliefs are fairly symmetrical while math and science teachers' perceptions of expectation are moderately skewed. All skewness and kutosis values were less than the absolute value of +/- 0.75, implying normal distribution.

To test to see if similarity in mean and standard deviation was due to sample size, I randomly sampled ten percent of all cases. While there was slightly more variation, the means were still very close to zero and standard deviations were almost identical to 1. Tables 18a and 18b present information regarding teachers' beliefs and expectations.

Table 18a. ***Teachers' Math and Science Beliefs and Expectations***

	All Teachers		Random Sample of Cases	
	Mean	SD	Mean	SD
Math Teachers				
Beliefs	-0.0007	1.0000	-0.0436	1.0412
Perceptions of Teacher Expectations	0.0017	0.9999	0.0150	0.9986
Science Teachers				
Beliefs	-0.0003	1.0007	0.0540	0.9773
Perceptions of Teacher Expectations	0.0001	1.0007	-0.0082	0.9951

Overall, with regard to both math and science teacher beliefs and perceptions of expectation, private school teachers had higher mean scores. Looking at school locale, suburban and rural teachers had higher math beliefs than those in cities and towns, with suburban teachers having the highest (M = 0.09) and city teachers having the lowest (M = -0.11). Similarly, suburban and rural teachers had higher math expectation than those in cities and towns, with rural teachers having the highest (M = 0.11) and city teachers having the lowest (M = -0.08). With regard to science teachers, suburban and city teachers had higher science beliefs than those in towns and rural locations, with suburban teachers having the highest (M = 0.06) and town teachers having the lowest (M = -0.21). Rural and suburban teachers had higher science expectation than those in cities and towns, with rural teachers having the highest (M = 0.05) and town teachers having the lowest (M = -0.04).

Considering geographic location, Midwest and Southern teachers had higher math beliefs than those in the Northeast and West, with Southern teachers having the highest (M = 0.06) and teachers in the West having the lowest (M = -0.12). Northeastern and Southern teachers had higher math expectation than those in the Midwest and West, with Northeastern teachers having the highest (M = 0.09) and teachers in the West having the lowest (M = -0.14). With regard to science teachers, Southern and Western teachers had higher science beliefs than those in the Northeast and Midwest, with Southern teachers having the highest (M = 0.06) and Northeastern teachers having the lowest (M = -0.10). Finally, the only group with teacher perceptions of expectation above average was those in the South (M = 0.14). Teachers in the Midwest had the lowest score for perceptions of teacher expectations (-0.12).

When testing to see if there were significant differences in math teachers' beliefs and perceptions of teacher expectations based on school type, locale, and geographical location, each regression returned significance with *p* values less than .001. The same held true when examining science teacher beliefs and perceptions of expectations.

Table 18b. ***Math and Science Teacher Beliefs and Perceptions of Expectation***

	School Type		School Locale				School Geographical Region			
	Public	Private	City	Suburb	Town	Rural	Northeast	Midwest	South	West
	M	M	M	M	M	M	M	M	M	M
Teacher Beliefs and Expectations	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)	(SD)
Math Teachers										
Beliefs	-0.03 (1.01)	0.43 (.78)	-0.11 (1.03)	0.09 (1.00)	-0.01 (0.97)	0.03 (0.96)	-0.01 (1.04)	0.03 (0.90)	0.06 (0.97)	-0.12 (1.10)
Perceptions of Teacher Expectations	-0.04 (1.01)	0.51 (.73)	-0.08 (1.04)	0.04 (0.97)	-0.10 (1.01)	0.11 (0.95)	0.09 (0.96)	-0.01 (1.00)	0.05 (1.03)	-0.14 (0.96)
Science Teachers										
Teacher Beliefs	-0.03 (1.00)	0.42 (0.87)	0.03 (1.07)	0.06 (1.01)	-0.21 (0.90)	-0.01 (0.93)	-0.10 (1.06)	-0.01 (0.93)	0.06 (1.01)	0.00 (1.00)
Perceptions of Teacher Expectations	-0.03 (1.00)	0.31 (0.91)	-0.03 (1.05)	0.01 (1.01)	-0.04 (0.91)	0.05 (0.96)	-0.03 (1.02)	-0.12 (0.97)	0.14 (1.02)	-0.07 (0.95)

Core STEM Career Development Components

The core components of STEM career development are self-efficacy, outcome-expectation, and interest. When analyzing the descriptive statics of each of these elements, for math and science respectively, the means showed to be nearly zero with a standard deviation of nearly one. This was expected, as these variables were standardized. Further, analysis of skewness and kurtosis of each component yielded similar findings. All were less than the absolute value of +/- 0.5, implying normal distribution.

To test to see if similarity in mean and standard deviation was due to sample size, I randomly sampled ten percent of all cases. While there was slightly more variation, the means were still very close to zero and standard deviations were almost identical to 1. Table 19a below presents the means and standard deviations using the full sample as well as a random sample of ten percent of cases.

Table 19a. ***Students' Math and Science Self-Efficacy, Outcome-Expectation, and Interest***

	All Students		Random Sample of Cases	
	Mean	SD	Mean	SD
Core Math Career Development Components				
Math Self-efficacy	-0.0007	1.0004	0.0217	0.9900
Math Outcome Expectation	-0.0025	0.9984	0.0404	1.0004
Math Interest	0.0009	1.0000	0.0661	0.9808
Core Science Career Development Components				
Science Self-efficacy	-0.0014	0.9987	0.0177	0.9499
Science Outcome Expectation	-0.0016	0.0700	-0.0019	0.0706
Science Interest	0.0009	1.0000	-0.0174	0.9806

*Weighted by W2Student

With regard to math self-efficacy, males had higher self-efficacy than females, with male students' self-efficacy in their math courses being above average and females being below. Black students had the highest level of math self-efficacy, followed by Asians, Whites and

Latinos. Black and Asian students' self-efficacy was above average, while White and Latino students were below average. Looking across socio-economic quintiles, students in the highest quintile had the highest self-efficacy, while students in the 3rd quintile had the lowest.

Examining math outcome expectation, males had higher outcome expectations than females, with male students' outcome expectation of their math courses slightly above average and females being slightly below. Black students had the highest level of outcome expectation, followed by Asians, Latinos and Whites. Black and Asian students' outcome expectation were above average, while White students' was below average. Latino students' were right on average. Looking across socio-economic quintiles, students in the lowest quintile had the highest outcome expectation, while students in the 3rd quintile had the lowest.

Analyzing math interest, males and females had identical mean scores. Asian students had the highest math interest, followed by Black and Latino students, with White students having the lowest. Across SES quintiles, students in the highest and lowest quintiles had nearly identical interests, which were higher than those in the other quintiles. Students in the second quintile had the lowest.

With regard to science self-efficacy, males had higher self-efficacy than females, with male students' self-efficacy in their science courses being above average and females being below. Black students had the highest level of science self-efficacy, followed by Asians, Whites and Latinos. Black, Asian, and White students' self-efficacy were above average, while Latino students' was below average. Looking across socio-economic quintiles, students in the highest quintile had the highest self-efficacy, while students in the lowest quintile had the lowest.

Examining science outcome expectation, males and female students had identical science outcome expectations. Asian students had the highest level of outcome expectation, followed by

Blacks, Whites and Latinos. Black and Asian students' outcome expectation was above average, while Latinos students' was below average. White students' science outcome expectations were right on average. Looking across socio-economic quintiles, all students' science outcome expectations were right on average, with the exception of those in the highest quintile. Their science outcome expectation was slightly above average.

Finally, analyzing science interest, male students' interest was above average while female students' was below average. Asian students had the highest science interest, followed by White, Black and Latino students. Across SES quintiles, students in the highest quintile had the highest science interest. Conversely, students in the second quintile had the lowest. Table 19b below provides the mean statistics for students' math and science self-efficacy, outcome expectation, and interest.

Table 19b. ***Mean of Students' Self-Efficacy, Outcome Expectation, and Interest***

	Gender		Race/Ethnicity				Socio-economic Quintiles				
	Male	Female	White	Asian	Black	Latino	Lowest	2nd	3rd	4th	Highest
Core SCCT Components											
Math											
Self-efficacy	0.11	-0.11	-0.02	0.13	0.16	-0.06	-0.01	0.03	-0.07	0.00	0.14
Outcome Expectation	0.02	-0.02	-0.07	0.14	0.26	0.00	0.09	0.00	-0.08	-0.01	0.02
Interest	0.00	0.00	-0.06	0.33	0.18	0.02	0.07	-0.07	-0.03	0.00	0.08
Science											
Self-efficacy	0.09	-0.09	0.01	0.09	0.12	-0.13	-0.05	0.01	0.03	0.02	0.18
Outcome Expectation	0.00	0.00	0.00	0.02	0.01	-0.01	0.00	0.00	0.00	0.00	0.01
Interest	0.04	-0.03	0.02	0.17	0.01	-0.07	-0.04	-0.08	0.08	0.05	0.10

Research Question 1
(RQ1): Are there differences in STEM career intentions or STEM major selections, based on race/ethnicity, gender, or socio-economic status?

Intent to Pursue a STEM Career

Analyzing students' career pursuit intentions, about 34 percent of students reported that they intended to select a career that was in a STEM field. Looking at within racial/ethnic group distributions, Asian students had the highest percentage of students intending to pursue a STEM career at more than 40 percent. White, Black, and Latino students had similar within-group percentage distributions, with 34, 35, and 32 percent of students intending to pursue a STEM career, respectively. When considering gender, and particularly looking at within-group distributions, a higher percentage of females intended to pursue a career in STEM than males. Only 26 percent of males intended to select a STEM occupation compared to 43 percent of female students. Finally, analyzing STEM pursuit intentions by socio-economic quintiles, percentages increased with each quintile, with 31.4 percent of students within the lowest quintile intending to pursue a career in STEM, and 41.6 in the highest quintile. Tables 20-23 display information regarding students' intent to pursue a STEM career, including findings based on race/ethnicity, gender, and socio-economic status.

STEM Occupational Intentions by Sub-domain

The occupational domain within STEM selected by the highest percentage of students was the health field, with 21.8 percent of students reporting their intent to pursue a health-related occupation. Next, 8.5 percent of students intended to select a career in a life and physical sciences, engineering, mathematics, or information technology occupation, followed by three percent in an occupation that is split between two STEM sub-domains, and .3 percent in an unspecified STEM sub-domain. Due to small numbers, students who reported intentions of selecting a STEM occupation that was split between two domains, or an occupation in a STEM sub-domain that was unspecified were combined, which is represented in tables 21-23 as *Other*.

Table 20. ***Selection of a STEM Occupation***

STEM Sub-domain	N	%
Not STEM Occupation	2,687,120	65.8
Life and Physical Sciences, Engineering, Mathematics, and Information Technology Occupations	348,091	8.5
Health Occupations	891,767	21.8
Split Across Two-Sub-domains	123,065	3.0
Unspecified STEM Sub-domain	10,753	0.3
Uncodeable	21,345	0.5

*Weighted by W2Student

STEM Occupational Intentions by Gender

Looking at gender, most female students intend to pursue a health occupation (79.4 percent) whereas male students were more likely to select a career in life and physical sciences, engineering, mathematics, and information technology (49.1 percent). Consequently, males were nearly three times more likely to report that they intended to select an occupation in life and physical sciences, engineering, mathematics, and information technology. The reverse holds true for females with regard to health occupations.

Table 21. ***Selection of STEM Occupation by Gender***

	Gender	
	Male Row % (Column %)	Female Row % (Column %)
Selection of STEM Occupation	37.7 (25.7)	62.3 (42.6)
STEM Sub-domain Selection		
Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations	74.1 (49.1)	25.9 (10.4)
Health Occupations	22.5 (38.2)	77.5 (79.4)
Other	42.9 (12.7)	57.1 (10.2)

*Weighted by W2Student

STEM Occupational Intentions by Race/Ethnicity

Health occupations were highest reported as the STEM occupational sub-domain students intended to pursue for all racial/ethnic subgroups. When comparing students who are intending to select health occupations across racial/ethnic groups, the distribution is similar to that of the population. However, when looking at life and physical sciences, engineering, mathematics, and information technology, Whites and Asians are slightly over-represented.

Table 22. ***Selection of STEM Occupation by Race***

	Race/ethnicity			
	White	Black	Latino	Asian
	Row % (Column %)	Row % (Column %)	Row % (Column %)	Row % (Column %)
Selection of STEM Occupation	56.8 (34.2)	15.5 (35.3)	23.1 (32.3)	4.6 (40.4)
STEM Sub-domain Selection				
Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations	63.5 (27.5)	11 (17.5)	20.8 (22.1)	4.6 (24.7)
Health	54.1 (61.2)	17.7 (73.2)	23.3 (64.8)	5 (68.8)
Other	57.4 (11.3)	12.9 (9.3)	27 (13.1)	2.7 (6.5) !

*Weighted by W2Student
! Interpret data with caution. Estimate is unstable because the standard error represents more than 30 percent of the estimate.

STEM Occupational Intentions by Socio-Economic Status

Health occupations were highest reported as the STEM occupational sub-domain students intended to pursue for all socio-economic subgroups. When comparing students who were intending to select health occupations across socio-economic groups, the distribution is similar to that of the population distribution. Examining life and physical sciences, engineering, mathematics, and information technology, however, students in the highest socio-economic quintile were nearly twice as likely than those in the lowest quintile to report that they intended to select an occupation in this sub-domain.

Table 23. ***Selection of STEM Occupation by Socio-economic Status***

	Socio-economic Quintiles				
	Lowest quintile Row % (Column %)	Second quintile Row % (Column %)	Third quintile Row % (Column %)	Fourth quintile Row % (Column %)	Highest quintile Row % (Column %)
Selection of STEM Occupation	20.6 (31.4)	16.0 (33.0)	17.1 (36.9)	19.3 (37.4)	27.0 (41.6)
STEM Sub-domain Selection					
Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations	17.2 (22.0)	14.5 (23.8)	17 (26.1)	17.6 (24.0)	33.7 (32.8)
Health Occupations	21.7 (66.9)	16.6 (65.7)	16.7 (62.1)	20.2 (66.3)	24.7 (57.9)
Other	22 (11.1)	16.2 (10.5)	19.4 (11.8)	18 (9.7)	24.3 (9.4)

*Weighted by W2Parent

Life and Physical Sciences, Engineering, Mathematics, and Information Technology Sub-domain

There is a difference between intending to pursue a career in core STEM domains, i.e. life and physical sciences, engineering, mathematics, and information technology occupations, and pursuing a profession in the medical sciences, i.e., health occupations. Since these are two very distinct sub-domains of STEM, where the former is what is traditionally conceptualized when using the construct *STEM* while the latter is typically conceptualized as medicine, I find it important to look more closely at the distribution of individuals who specifically selected life and physical sciences, engineering, mathematics, and information technology.

Looking at the entire student population, 8.5 percent of student reported their intention to pursue a career in life and physical sciences, engineering, mathematics, and information technology. Examining gender, about 12 percent of all males reported their intention to pursue this occupational sub-domain, while only slightly more than 4 percent of females indicated similarly. Looking across gender, males made up nearly three-fourths of individuals planning to select an occupation in the life and physical sciences, engineering, mathematics, and information technology.

Observing race, ten percent of Asian students, nine percent of White, seven percent Latino, and six percent of Black students reported their intention of selecting a career in this STEM occupational sub-domain. Whites and Asians were slightly over-represented, comprising nearly 64 and 5 percent, respectively, of individuals intending to pursue a career in life and physical sciences, engineering, mathematics, and information technology. Blacks and Latinos were slightly under-represented, and represented 11 and 21 percent of students, respectively.

Analyzing socio-economic status, individuals in the highest socio-economic quintile had the largest percent of students within their respective socio-economic subgroup intending to pursue a career in life and physical sciences, engineering, mathematics, and information technology (nearly 13 percent). The reverse holds true for students in the lowest socio-economic quintile (6 percent). When comparing the distributions across socio-economic quintiles, the first and second quintiles and the third and fourth quintiles were fairly similar in their intent to pursue a career in this sub-domain, respectively. However, the highest quintile contributed the most individuals, encompassing more than 30 percent of all students intending to pursue a career in life and physical sciences, engineering, mathematics, and information technology. Table 24 below provides details regarding students interested in occupations in life and physical sciences, engineering, mathematics, and information technology.

Table 24. ***Occupation in Life and Physical Sciences, Engineering, Mathematics, and Information Technology***

Occupation in Life and Physical Sciences, Engineering, Mathematics, and Information Technology Sub-Domain	Group Percentages	
	Within Group %	Between Group %
All Students	8.5	-
Racial Subgroups		
Asian	10.0	4.6
Black	6.3	11.0
Latino	7.1	20.8
White	9.4	63.5
Gender		
Male	12.2	74.1
Female	4.4	25.9
Socio-economic Quintiles		
Lowest quintile	6.1	14.2
Second quintile	6.5	15.2
Third quintile	7.9	18.5
Fourth quintile	9.3	22.0
Highest quintile	12.8	30.1

*All, race, and gender weighted by W2Student.
*Socio-economic status weighted by W2Parent
Note: Within group percentages are equivalent to column percentages in prior tables. Similarly, between group percentages are equivalent to row percentages. Data are presented differently in this table due to size.

Intersectional Analysis of Intent to Pursue a STEM Career

Race/ethnicity and Gender

When analyzing the intersection between race and gender, it is apparent that every female racial subgroup had higher percentages of individuals intending to select a STEM occupation than male racial subgroups. The male subgroup with the highest percentage of members intending to pursue a STEM occupation (Asians males, with 36 percent) was still less than the female subgroup with the least percentage of members intending to select a STEM occupation (Latino females, 41 percent). Blacks had the largest gendered gap, where 72 percent of Black students intending to pursue a STEM career were female. In contrast, Asians had the smallest gendered gap, which was about 12 percent.

Males in all racial/ethnic groups most intended to pursue occupations in life and physical sciences, engineering, mathematics, and information technology, whereas females in all racial/ethnic groups intended to pursue health occupations. The difference of selection between health occupations or life and physical sciences, engineering, mathematics, and information technology occupations was higher for female groups than male groups, with black females having the largest margin at nearly 75 percent. Latino males had the smallest occupational margin of all racial gendered groups, with only a 3 percent difference between those who selected between these two STEM sub-domains.

Table 25. ***STEM Occupation Selection with Intersection among Race and Gender***

	Intersection between Race and Gender Row % (Column %)							
	White		Black		Latino		Asian	
	Male	Female	Male	Female	Male	Female	Male	Female
Selection of STEM Occupation	39.8 (26.6)	60.2 (42.1)	28.1 (21.7)	71.9 (46.8)	37.4 (24.1)	62.6 (40.6)	43.8 (35.9)	56.2 (44.8)
STEM Sub-domain Selection								
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	77.7 (53.7)	22.3 (10.2)	65.1 (40.5)	34.9 (8.5)	71.9 (42.5)	28.1 (9.9)	78.1 (44.0)	21.9 (9.6)
Health	22.3 (34.4)	77.7 (78.9)	18.3 (47.6)	81.7 (83.2)	22.8 (39.5)	77.2 (79.9)	33.4 (52.5)	66.6 (81.6)
Other	41.8 (11.9)	58.2 (10.9)	35.7 (11.8)	64.3 (8.4)	51.2 (17.9)	48.8 (10.2)	23.7 (3.5)	76.3 (8.8)

*Weighted by W2Student
Note: Row percentages are within each race/ethnicity, respectively.

Gender and Socio-economic Status

When analyzing the intersection between gender and socio-economic status of students intending to pursue a STEM occupation, across all quintiles and within the gendered subpopulations, females had higher percentages of members that intended to select STEM occupations. Across all quintiles, female students selected health occupations most. With the exception of the third quintile, male students most often selected occupations in the life and physical sciences, engineering, mathematics, and information technology. The first quintile has the largest gap between male and female students within life and physical sciences, engineering, mathematics, and information technology occupational category (69 percent). The second quintile has the largest gap between male and female students wanting to pursue health occupations (75 percent). When comparing quintiles, the highest quintile had the highest percentage of males that intend to pursue a career in life and physical sciences, engineering, mathematics and information technology. Of female students within the lowest socio-economic quintile that intend to pursue a STEM occupation, only about 5 percent selected an occupation in life and physical sciences, engineering, mathematics, and information technology, the lowest of any group.

Table 26. ***STEM Occupation Selection with Intersection between Socio-economic Status and Gender***

	Intersection between Socio-economic Status and Gender Row % (Column %)									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
STEM Occupation	35.8 (22.6)	64.2 (40.1)	28.0 (18.3)	72.0 (48.2)	39.2 (28.6)	60.8 (45.4)	37.4 (29.0)	62.2 (45.3)	43.1 (35.1)	56.9 (48.3)
STEM Sub-Domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	84.5 (51.8)	15.5 (5.3)	65.2 (55.4)	34.8 (11.5)	61.0 (40.6)	39.0 (16.7)	76.7 (49.2)	23.3 (8.9)	74.9 (56.9)	25.1 (14.5)
Health	18.0 (33.6)	82.0 (85.5)	12.6 (29.5)	87.4 (79.7)	30.4 (48.2)	69.6 (71.0)	24.5 (43.5)	75.5 (79.9)	26.9 (36.0)	73.1 (74.4)
Other	47.0 (14.6)	53.0 (9.2)	40.1 (15.0)	59.9 (8.7)	37.0 (11.2)	63.0 (12.2)	28.2 (7.3)	71.8 (11.1)	32.5 (7.1)	67.5 (11.1)

*Weighted by W2Parent
Note: Row percentages are within each quintile, respectively.

Race/ethnicity and Socio-economic Status

Examining STEM career intentions by race and socio-economic status, within the lowest socio-economic quintile, there were similar percentages of individuals intending to select a STEM occupation across all races. However, within the highest quintile, Blacks and Asians were more similar (about 52 percent), while Whites and Latinos were comparable (32-33 percent). In addition, Whites and Latinos had more of an equal distribution across quintiles. Black students' intention to pursue a STEM career increased as their socio-economic level increased, while all others were more varied along socio-economic categories.

Across all racial quintiles, with the exception of Asians in the third quintile, more students choose occupations in the health fields than life and physical sciences, engineering, mathematics, and information technology. Within the Black student population, of students intending to select an occupation in the life and physical sciences, engineering, mathematics, and information technology, most students were in the highest socio-economic quintile. Conversely, of students selecting a health occupation, the highest population of Black students was in the lowest quintile. For White students, most students intending to select an occupation in either the life and physical sciences, engineering, mathematics, and information technology or health occupations were in the highest socio-economic quintile. In contrast, most Latino students intending to pursue a career in either of those occupational sub-domains were in the lowest socio-economic quintile.

Table 27a. ***STEM Occupation Selection with Intersection between Race and Socio-economic status***

	Intersection Between Race and Socio-economic Status Row % (Column %)									
	White					Black				
	Lowest quintile	Second quintile	Third quintile	Fourth quintile	Highest quintile	Lowest quintile	Second quintile	Third quintile	Fourth quintile	Highest quintile
Selection of STEM Occupation	11.6 (33.3)	14.2 (32.0)	17.4 (35.0)	22.9 (36.8)	34.0 (39.6)	27.0 (29.4)	17.8 (38.0)	21.7 (45.4)	15.4 (47.1)	18.0 (51.6)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	9.8 (24.4)	11.4 (23.1)	18.0 (29.8)	21.3 (26.9)	39.5 (33.4)	15.7 (9.3)	13.4 (12.0)	17.5 (12.9)	13.7 (14.2)	39.6 (35.0)
Health	11.9 (62.2)	16.0 (68.5)	16.7 (58.5)	24.2 (64.2)	31.3 (55.7)	31.1 (82.9)	17.7 (71.3)	21.7 (71.7)	16.1 (75.5)	13.4 (53.6)
Other	14.7 (13.4)	11.2 (8.4)	19.4 (11.8)	19.5 (9.0)	35.1 (10.8)	17.4 (7.8)	24.7 (16.7)	27.8 (15.4)	13.2 (10.3)	17.0 (11.4)

*Weighted by W2Parent

Note: Row percentages are within each race/ethnicity, respectively

Table 27b. ***STEM Occupation Selection with Intersection Between Race and Socio-economic Status Cont'd***

	Intersection Between Race and Socio-economic Status Row % (Column %)									
	Latino					Asian				
	Lowest quintile	Second quintile	Third quintile	Fourth quintile	Highest quintile	Lowest quintile	Second quintile	Third quintile	Fourth quintile	Highest quintile
Selection of STEM Occupation	41.1 (32.1)	20.6 (31.5)	15.4 (35.9)	12.7 (32.5)	10.2 (36.5)	10.5 (31.1)	14.2 (63.4)	13.3 (39.8)	19.0 (50.2)	43.1 (52.3)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	41.7 (26.1)	24.8 (31.1)	15.4 (25.8)	7.2 (14.6)	10.8 (27.3)	19.5 (41.1)	22.4 (34.7)	30.4 (50.6)	3.5 (4.0)	24.2 (12.4)
Health	40.3 (61.8)	19.0 (58.2)	15.6 (64.0)	14.3 (70.9)	10.7 (66.4)	8.3 (58.4)	11.9 (61.2)	8.4 (46.5)	24.4 (94.3)	46.9 (79.7)
Other	44.3 (12.1)	19.6 (10.7)	14.1 (10.3)	16.4 (14.5)	5.6 (6.2)	1.2 (0.5)	12.2 (4.0)	8.3 (2.9)	6.6 (1.6)	71.8 (7.9)

*Weighted by W2Parent
Note: Row percentages are within each race/ethnicity, respectively

Race/ethnicity, Gender, and Socio-economic Status

The intersection among race, gender, and socio-economic status yielded similar results to those discussed prior. Across all races, a higher percentage of female students within each quintile intended to pursue STEM occupations than male students within the same quintiles. With a few exceptions, males are highest represented in life and physical sciences, engineering, mathematics, and information technology, while women are highest represented in health occupations. Males in the highest quintiles tended to most select occupations in life and physical sciences, engineering, mathematics, and information technology, with the exception of Asian males. Males in the lowest quintiles tended to also select occupations in that STEM occupational sub-domain. Females in all socio-economic quintiles and across all races tended to select occupations in the health fields most.

White males in all socio-economic quintiles selected life and physical sciences, engineering, mathematics, and information technology most. The same holds true for Latino males, except those in the fourth quintile. In contrast, Black males in the middle quintiles most often selected occupations in the health fields. Similarly, most Asian males in the second, fourth, and fifth quintiles intend to pursue an occupation in the health field.

Table 28 below presents descriptive findings of students' intended STEM occupational pursuits, with intersections among their diverse identity categories. Due to the large size of this table, it has been divided into smaller subsets by race (Tables 28a-d).

Table 28a. ***STEM Occupation Selection with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender Row % (Column %)									
	White									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Selection of STEM Occupation	35.4 (22.7)	64.6 (44.6)	24.9 (15.9)	75.1 (48.1)	45.3 (29.3)	54.7 (41.6)	39.7 (30.1)	60.3 (43.0)	45.4 (34.6)	54.6 (45.0)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	79.8 (54.9)	20.2 (7.6)	59.6 (55.3)	40.4 (12.5)	68.3 (44.9)	31.7 (17.3)	81.4 (54.0)	18.6 (8.3)	80.7 (59.5)	19.3 (11.8)
Health	14.0 (24.5)	86.0 (82.9)	10.0 (27.5)	90.0 (82.1)	34.6 (44.7)	65.4 (69.8)	23.4 (37.9)	76.6 (81.5)	26.6 (32.7)	73.4 (74.9)
Other	54.4 (20.5)	45.5 (9.4)	51.4 (17.2)	48.6 (5.4)	40.0 (10.4)	60.0 (12.9)	31.3 (7.1)	68.7 (10.2)	33.0 (7.9)	67.0 (13.3)

*Weighted by W2Parent

Note: Row percentages are within each quintile, respectively

Table 28b. ***STEM Occupation Selection with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender Row % (Column %)									
	Black									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Selection of STEM Occupation	18.7 (14.3)	81.3 (38.8)	14.5 (11.2)	85.5 (64.0)	25.2 (26.8)	74.8 (59.4)	39.0 (40.8)	61.0 (52.3)	34.5 (42.7)	65.5 (58.0)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	82.7 (41.0)	17.3 (2.0)	37.2 (30.8)	62.8 (8.8)	53.3 (27.1)	46.7 (8.0)	66.4 (24.2)	33.6 (7.8)	46.5 (47.2)	53.5 (28.6)
Health	8.9 (39.5)	91.1 (92.9)	7.6 (37.3)	92.4 (77.1)	24.4 (69.3)	75.6 (72.6)	33.6 (65.0)	66.4 (82.2)	27.1 (42.1)	72.9 (59.7)
Other	46.9 (19.5)	53.1 (5.1)	27.7 (31.9)	72.3 (14.1)	5.8 (3.5)	94.2 (19.4)	40.9 (10.8)	59.1 (10.0)	32.4 (10.7)	67.6 (11.7)

*Weighted by W2Parent
Note: Row percentages are within each quintile, respectively

Table 28c. ***STEM Occupation Selection with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender Row % (Column %)									
	Latino									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Selection of STEM Occupation	42.9 (26.3)	57.1 (38.5)	39.2 (23.1)	60.8 (41.1)	35.7 (28.4)	64.3 (42.0)	26.7 (18.3)	73.3 (45.2)	26.0 (18.9)	74.0 (54.1)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	86.2 (52.4)	13.8 (6.3)	81.5 (64.6)	18.5 (9.4)	33.3 (24.0)	66.7 (26.7)	93.1 (51.0)	6.9 (1.4)	58.5 (61.5)	41.5 (15.3)
Health	24.5 (35.2)	75.5 (81.8)	16.9 (25.1)	83.1 (79.6)	31.1 (55.7)	68.9 (68.6)	17.7 (47.0)	82.3 (79.6)	13.5 (34.5)	86.5 (77.6)
Other	43.9 (12.4)	56.1 (11.9)	37.5 (10.2)	62.5 (11.0)	70.4 (20.3)	29.6 (4.7)	3.7 (2.0)	96.3 (19.0)	16.6 (4.0)	83.4 (7.0)

*Weighted by W2Parent
Note: Row percentages are within each quintile, respectively

Table 28d. ***STEM Occupation Selection with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender Row % (Column %)									
	Asian									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Selection of STEM Occupation	57.2 (33.0)	42.8 (28.9)	64.4 (73.0)	35.6 (51.2)	66.9 (38.8)	33.1 (41.9)	23.5 (28.3)	76.5 (65.9)	37.4 (45.7)	62.2 (57.2)
STEM Sub-domain Selection										
Life and Physical Sciences, Engineering, Mathematics, and Information Technology	94.6 (67.9)	5.4 (5.2)	91.1 (49.1)	8.9 (8.7)	100 (75.6)	0 (0)	92.8 (15.9)	7.2 (0.4)	77.0 (25.5)	23.0 (4.6)
Health	30.5 (31.1)	69.5 (94.8)	53.6 (50.9)	46.4 (80.0)	31.8 (22.1)	68.2 (95.8)	19.7 (79.3)	80.3 (98.9)	32.1 (68.3)	67.9 (86.6)
Other	100.0 (0.9)	0 (0)	0 (0)	100 (11.4)	52.5 (2.3)	47.5 (4.2)	67.8 (4.8)	32.2 (0.7)	29.3 (6.2)	70.7 (8.9)

*Weighted by W2Parent

Note: Row percentages are within each quintile, respectively

Intent to Select a STEM Major

Twenty-one percent of students intend to select a STEM major in college. Male students make up 66.5 percent of students intending to select a STEM major. Of the male student subpopulation, 29.5 percent intended to select a STEM major, while only 13.2 percent of female students reported similarly.

Looking specifically at the White, Black, Latino, and Asian subpopulations, of students reporting their intention to select a STEM major, 64.9 percent were White, 18.1 Latino, 8.3 Black, and 8.3 Asian. Looking at within-race distributions, the Asian student population had the highest percentage of students intending to select a STEM major (36.2), followed by Whites (22.4), Latinos (17.2), and Blacks (13.7). This further demonstrates that Whites, Asians, and males are more likely to engage in STEM pursuits, and thus are over-represented, whereas Blacks, Latinos, and females continue to be under-represented.

Considering socio-economic status, students from the lowest socio-economic quintiles were the least represented of students who selected a STEM major (9.7 and 9.8 percent for lowest and 2nd quintile, respectively) and also has the least amount of students within their respective groups to select a STEM major (13.3 and 16 percent, respectively). Conversely, students in the highest socio-economic quintile most represented students who selected a STEM major (42.7 percent). Nearly 30 percent of students within the highest socio-economic quintile selected a STEM major. Table 29 below provides descriptive information regarding STEM major selection by race, gender, and socio-economic status.

Table 29. ***Selection of STEM Major by Race/ethnicity, Gender, and Socio-economic Status***

	All %	Race % (Row %)				Gender % (Row %)		Socio-economic Status % (Row %)				
	All	White	Black	Latino	Asian	Male	Female	Lowest	2nd	3rd	4th	Highest
Select STEM Major	20.9	22.4 (64.9)	13.7 (8.3)	17.2 (18.1)	36.2 (8.3)	29.5 (66.5)	13.2 (33.5)	13.3 (9.7)	16.0 (9.8)	16.4 (12.2)	25.5 (25.7)	29.4 (42.7)

*Race and Gender weighted by W3Student, SES by W2Parent

Note: Row percentages are within race, gender, and socio-economic status, respectively.

Intersectional Analysis of STEM Major Selection

Race and Gender

Considering the intersection between race and gender, Asian males had the highest within-group percentage of students who intended to select a STEM major (42.8), while Latino females had the lowest (8.1). Additionally, Asian female students (30.2) had higher within-group percentages than Latino and Black males (27.9 and 19.4, respectively), and were very close to, but slightly less than that of White males (32). Tables 30 below present students' intention to select a STEM major in college with race intersected with gender.

Table 30. ***Selection of STEM Major with Intersection Between Race and Gender***

	Intersection between Race and Gender %							
	White		Black		Latino		Asian	
	Male	Female	Male	Female	Male	Female	Male	Female
Intent to Select a STEM Major	32.0	13.8	19.4	11.1	27.9	8.1	42.8	30.2

*Weighted by W3Stuudent

Race/ethnicity, Gender, and Socio-economic Status

Across race and socio-economic status, males tended to have higher percentages of individuals intending to select a STEM major in college, with very few exceptions. Aside from females in the third quintile and males in the fourth, Asian students had higher percentages of students intending to select a major in STEM when analyzing across quintiles. Asian males in the second quintile had the highest percentage of students intending to select a STEM major in college overall (64.3) and Black females in the second quintile had the lowest (2.3).

In nearly each group, at least 22 percent of Asian students intended to select a STEM major. For three-quarters of Black students, less than 20 percent intended to pursue a STEM major across quintiles. The same holds true for half of all Latino students, of which four-fifths were made up of female students. Across quintiles, no group of White female students intended to select a STEM career at 19 percent or more.

Black female students in the highest quintile were more than 10 times as likely as those in the lowest quintile, more than four times as likely as those in the second quintile, and more than twice as likely as those in the third quintile to select a STEM major. Black male students in the highest quintile were nearly six times as likely than those in the lowest quintile, twice more likely than those in the second quintile, and nearly three times as likely as those in the third quintile to select a STEM major. With the exception of the third quintile, Black males had higher percentages of individuals intending to select a STEM major than Black females within each socio-economic quintile.

Latino males had higher percentages of individuals intending to select a STEM major in college than Latino females across all quintiles. Further, in the lowest three quintiles, Latino males were nearly five times as likely as their female counterparts to select a STEM major.

A higher percentage of Asian males in each of the lowest three quintiles intended to select a STEM major than those in the highest two quintiles. Conversely, there was a higher percentage of Asian females in the highest two quintiles than in the lowest three quintiles that intended to select a STEM major.

Across all quintiles, White males were at least twice as likely as their female counterparts to select a STEM major. The gap grew larger in the lower quintiles, where White males in the lowest quintile were more than four times as likely as White females to select a STEM major. Table 31 below provides details regarding students' intent to select STEM majors with intersections among identity categories.

Table 31. ***Intent to Select STEM Major with Intersection Among Race, Socio-economic Status, and Gender***

	Intersection Among Race, Socio-economic Status, and Gender									
	Lowest quintile		Second quintile		Third quintile		Fourth quintile		Highest quintile	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Race	%	%	%	%	%	%	%	%	%	%
White	33.3	7.8	25.3	8.4	24.6	11.1	34.2	14.7	39.2	18.8
Asian	43.3	23.0	64.3	22.1	54.5	6.9	26.8	53.1	36.5	37.5
Black	5.1	2.3	17.7	5.6	10.9	12.8	33.6	20.0	31.1	25.5
Latino	26.3	5.6	31.1	5.0	12.7	2.5	31.3	24.7	36.0	15.6

*Weighted by W2Parent

Summary of Research Question 1 Findings

Table 32 below presents a summary of findings for Research Question 1. The first column of the table includes each subset of the research question and associated hypotheses. The second column presents research findings. Finally, the last column of the table notes whether hypotheses were supported, provides an interpretation of what findings mean, and reports whether findings are consistent with the literature.

Table 32. ***Summary of Research Question 1 Findings***

Research Questions and Hypotheses	Results	Interpretation
RQ1a_part 1: Are there differences in STEM career intentions based on gender? H1a_part1: Males will intend to pursue STEM careers at higher percentages than female students.	Higher percentages of female students intended to pursue STEM careers. Females were more likely to intend to pursue health occupations, while males were more likely to intend to pursue occupations in life and physical sciences, engineering, mathematics, and information technology.	The hypothesis was not supported; males did not intend to pursue STEM occupations at higher rates than female students. However, while female students intended to pursue STEM at much higher rates than male students, females mostly intended to pursue health occupations. Conversely, males mostly intended to pursue life and physical sciences, engineering, mathematics, and information technology. This matches current workforce trends, particularly with regard to women's under-representation in the sciences, engineering, mathematics, and information technology.

Table 32. ***Summary of Research Question 1 Findings***

Research Questions and Hypotheses	Results	Interpretation
RQ1a_part2: Are there differences in STEM career intentions based on race/ethnicity? H1a_part2: Asian and White students will intend to pursue STEM careers at higher percentages than Black and Latino students.	Asians had the highest percentage of students across all race/ethnicities that intended to pursue STEM careers (40 percent). White, Black, and Latino students had similar percentages. (34, 35, and 32 percent, respectively). Across race, health occupations was the highest reported STEM occupational subdomain students intended to pursue. When considering life and physical sciences, engineering, mathematics, and information technology occupations, Whites and Asians were slightly over-represented.	The hypothesis was not fully supported. Asian students did intend to pursue STEM occupations at higher rates than Black and Latino students; however, Black students intended to pursue STEM at higher rates than Whites. Moreover, White, Black, and Latino students' STEM career intentions were nearly identical. Asian and White students' pursuits are consistent with the literature, while Black and Latino students' intentions are not.
RQ1a_part3: Are there differences in STEM career intentions based on socio-economic status? H1a_part3: Students in the highest socio-economic quintiles will intend to pursue STEM careers at higher percentages than those in the lowest socio-economic quintiles.	STEM career intentions increased with socio-economic status. Across socio-economic status, health occupations was the highest reported STEM occupational subdomain students intended to pursue. Students in the highest socio-economic quintile were nearly twice as likely than those in the lowest quintile to report that they intended to pursue occupations in life and physical sciences, engineering, mathematics, and information technology.	The hypothesis was supported; students in the highest socio-economic quintiles intended to pursue STEM careers at higher percentages than those in lower socio-economic quintiles. The margins were most substantial when looking at those in pursuit of careers in the life and physical sciences, engineering, mathematics, and information technology sub domain. These findings are consistent with the literature.

Table 32. ***Summary of Research Question 1 Findings***

Research Questions and Hypotheses	Results	Interpretation
RQ1b_part1: Are there differences in STEM major selection based on gender? H1b_part1: Males will select STEM careers at higher percentages than female students.	Male students were more than twice as likely to select a STEM major than female students. Two-thirds of those who selected a STEM major were males.	The hypothesis was supported. Male students selected STEM majors at higher percentages than female students. This is consistent with the literature.
RQ1b_part2: Are there differences in STEM major selection based on race/ethnicity? H1b_part2: Asian and White students will select STEM majors at higher percentages than Black and Latino students.	Asian and White students selected STEM majors at higher percentages than Black and Latino students. Asian students were more than twice as likely as Black and Latino students to select a STEM major.	The hypothesis was supported; White and Asian students were more likely to select STEM majors. Thus, they remain over-represented in STEM, whereas Blacks and Latinos continue to be under-represented. This is consistent with the literature.
RQ1b_part3: Are there differences in STEM major selection based on socio-economic status? H1b_part3: Students in the highest socio-economic quintiles will select STEM majors at higher percentages than those in the lowest socio-economic quintiles.	Students in the highest socio-economic quintiles selected STEM majors at higher percentages than students in the lowest socio-economic quintiles. In fact, STEM major selection increased with socio-economic status.	The hypothesis was supported; the likelihood of STEM major selection increased with students' socio-economic status. Findings are consistent with the literature.

Research Question 2
(RQ2): What is the relationship among cognitive, psychological, and environmental factors as related to high school students' intent to pursue a STEM career and selection of a STEM major?

Math and Science STEM Career Development Models' Fit Indices

Assessing model fit indices, it was concluded that both the math and science models were of high quality and fit well with the data. The AVIF and VIF indices for both models were below 3.3, indicating the models' overall predicative and explanatory quality. The GoF of both models, which is a measure of a model's explanatory power, had values greater than 0.36, indicating high explanatory power.

Four experimental indices, SPR, RSCR, SSR, and NLBCDR (Kock, 2015), were also included in the assessment of the math and science models in this research. The SPR index, which measures the extent to which a model is free from Simpson's paradox instances (Kock, 2015), indicated that the math model was at least 92.6 percent free from Simpson's paradox. Additionally, the science model was free from at least 84 percent of Simpson's paradox. This means that there is no indication of possible causality problems. There is no suggestion that hypothesized paths are implausible or reversed.

The RSCR index is a measure of the extent to which a model is free from negative R-squared contributions (Kock, 2015). Models with RSCR values equal to one indicate that there are no negative R-squared contributions to the model, which was the case for both the math and science model. This means that predictor variables are not reducing the percentage of variance explained.

Next, the SSR index, which measures the extent to which a model is free from statistical suppression instances (Kock, 2015), had a value of 1 for both models, indicating that all paths in the models were free from statistical suppression. This means that the absolute value of the path coefficient is not greater than that of the corresponding correlation of associated linked variables. In other words, there is no indication of possible causality problems.

Finally, the NLBCDR measures the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in a model (Kock, 2015). The NLBCDR value of the math model indicated that nearly 89 percent of path-related instances in the model supported that the reversed hypothesized direction of causality was weak or less. The same held true for 88 percent of path-related instances in the science model. This means that all hypothesized directions of causality are supported. Table 33 below provides all fit and quality indices of the math and science models.

Table 33. ***Math and Science Model Fit Indices***

	Model Fit and Quality Indices						
	Average block VIF (AVIF)	Average full collinearity VIF (AFVIF)	Tenenhaus GoF (GoF)	Simpson's paradox ratio (SPR)	R-squared contribution ratio (RSCR)	Statistical suppression ratio (SSR)	Nonlinear bivariate causality direction ratio (NLBCDR)
Math Model	1.200	1.197	0.435	0.926	1.000	1.000	0.889
Science Model	1.314	1.197	0.452	0.840	1.000	1.000	0.880

Interpretation of Findings

The path coefficients, as indicated by the numbers along each of the individual paths within the model, indicate the strength and direction of association between two variables. Thus, the higher a number is, the stronger the relationship. Further, positive path coefficients indicate positive relationships (i.e., an increase in one results in an increase in the other, and vice versa) and negative coefficients indicate inverse relationships (i.e., an increase in one results in a decrease in the other). Additionally, only path coefficients that are statistically significant, as indicated by *p*-values less than 0.05, are included in the models. While all others may not be included, exclusion does not suggest that the values of those path coefficients are absolute zero. It simply means that the relationships are not statistically significant. Within each of the tables presenting model estimates, path coefficients are represented by β.

Within the multi-group analysis, which examines differences in the model's path structure across groups (e.g., males and females in gender), special attention should be paid to the nature of the path coefficients to understand how groups compare. There may be path coefficients present for some groups but not others, indicating differences in the significance of relationships of variables between groups. For instance, self-efficacy may predict STEM career intentions for some groups (as evidenced by the path coefficients representing those groups being present in the model), but not others (as indicated by the absence of a path coefficient for that relationship in the model for other groups). Next, when particular relationships are significant for all groups in the model, there could be two outcomes. The first entails all coefficients for a particular path being different for all groups, a phenomenon called configural invariance. This means that the relationship is significant for all groups, but the association between the respective variables differs across groups. Conversely, when the coefficients are the same for all groups on a given path, this means that the relationship is significant for all groups, and that there is no difference in the association between variables across groups (i.e., the relationship is equivalent across groups).

Math Model

Intent to Pursue STEM

Students' math self-efficacy was directly and positively influenced by math aptitude, math identity, and math informal learning participation, with math identity being the strongest association. Similarly, math outcome expectation was directly and positively predicted by math aptitude, identity, informal learning participation, and self-efficacy, with the strongest association also being identity. Additionally, both math self-efficacy and math outcome expectation positively and significantly influenced math interest.

Intent to pursue a STEM career was significantly and positively influenced by math self-efficacy, math outcome expectation, math interest, and math teacher perceptions of expectations. Conversely, school informal STEM exposure and math teacher beliefs were not significant predictors of intent to pursue a STEM career. School informal STEM exposure negatively influenced the relationship between math interest and intent to pursue a STEM career, while math teacher beliefs and perceptions of expectations were not moderators at all.

Selection of a STEM Major

Selection of a STEM major was significantly and positively influenced by math self-efficacy, math outcome expectation, intent to pursue a STEM career, and school informal STEM exposure. It was not, however, influenced by math teacher beliefs or perceptions of teacher expectation. Intent to pursue a STEM career was the strongest predictor of STEM major selection. None of the environmental factors significantly moderated the relationship between intent to pursue a STEM career and STEM major selection.

<u>Science Model</u>

Intent to Pursue STEM

Students' science identity and science informal learning participation were positive predictors of science self-efficacy. Additionally, science identity and science informal learning positively and significantly influenced science outcome expectation. For both science self-efficacy and outcome expectation, science identity had the largest strength of association. Additionally, both science self-efficacy and science outcome expectation were significant and positive predictors of science interest.

Intent to pursue a STEM career was significantly and positively influenced by science self-efficacy, science outcome expectation, and science interest. While none of the environmental variables predicted students' intent to pursue a STEM career, science teacher beliefs moderated the relationship between science interest and STEM pursuit intentions.

Intent to Select a STEM Major

STEM major selection was significantly and positively influenced by science self-efficacy, science outcome expectation, intent to pursue a STEM career, and school informal STEM exposure, with the strongest predictor being intent to pursue a STEM career. None of the environmental variables moderated the relationship between intent to pursue a STEM career and selection of a STEM major.

Figure 6 below depicts the structural equation modeling of both the math-specific and science-specific STEM career development models. Additionally, Table 33 below presents the standardized estimates of both STEM career development models.

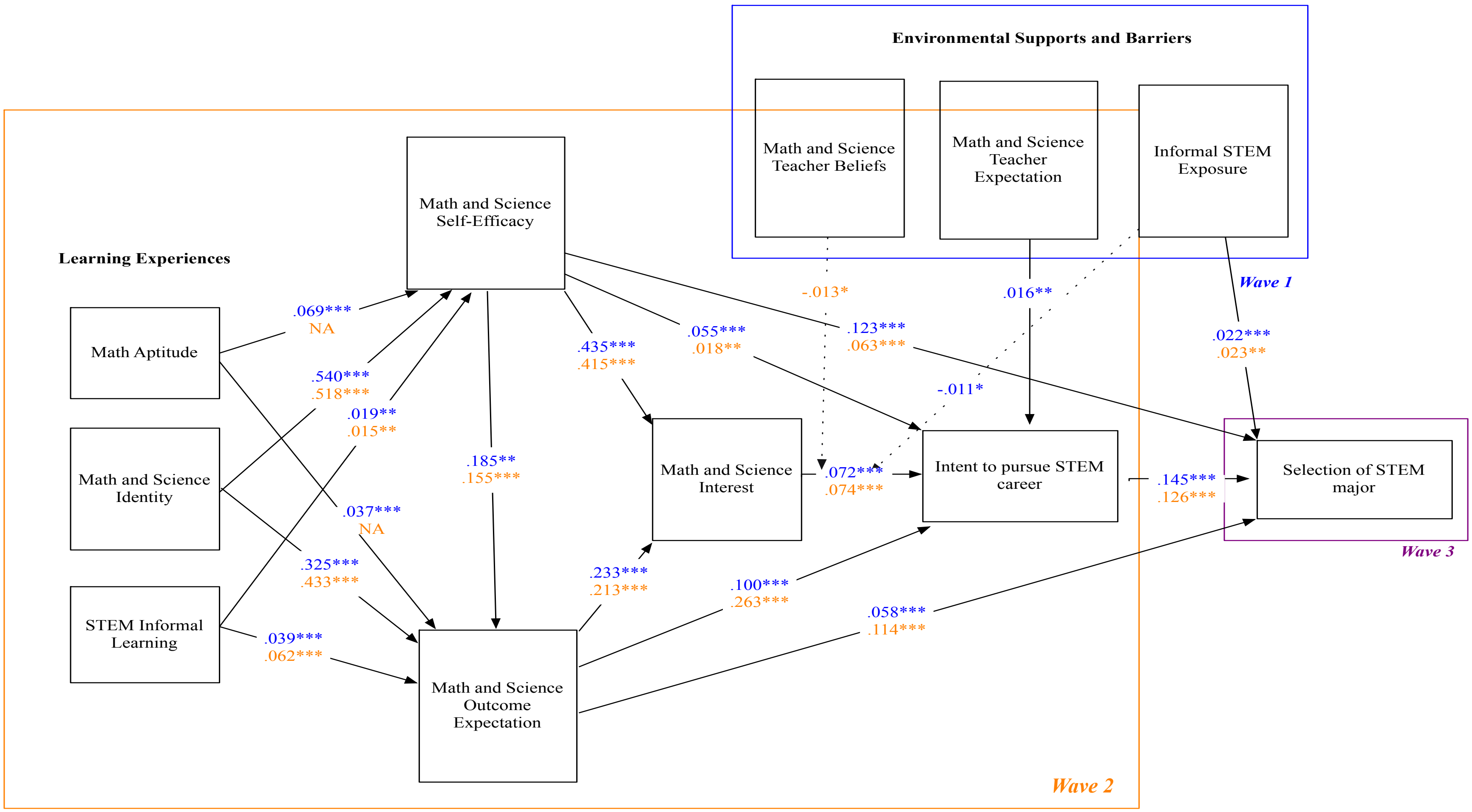


Figure 6. *Structural Equation Modeling of Math and Science STEM Career Development Model*
Note: Blue parameters represent math model, orange science model; $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***; insignificant paths, parameters omitted

Table 34. ***Standardized Estimates of STEM Career Development Models***

Model Effects	Math		Science	
	β	SE	β	SE
Self-Efficacy ON				
Math Aptitude	0.069***	0.007	NA	NA
Identity	0.540***	0.006	0.518***	0.006
Informal Learning Participation	0.019**	0.007	0.015**	0.007
Outcome Expectation ON				
Math Aptitude	0.037***	0.007	NA	NA
Identity	0.325***	0.006	0.433***	0.006
Informal Learning Participation	0.039***	0.007	0.062***	0.007
Self-Efficacy	0.185***	0.007	0.155***	0.007
Interest ON				
Self-Efficacy	0.435***	0.006	0.415***	0.006
Outcome Expectation	0.233***	0.006	0.231***	0.006
STEM Occupation ON				
Self-Efficacy	0.055***	0.007	0.018**	0.007
Outcome Expectation	0.100***	0.007	0.263***	0.006
Interest	0.072***	0.007	0.074***	0.007
Teacher Expectations	0.016**	0.007	0.009	0.007
School Informal STEM Exposure	0.004	0.007	0.004	0.007
Teacher Beliefs	-0.004	0.007	0.000	0.007
Teacher Beliefs*Interest	0.003	0.007	-0.013*	0.007
School Informal STEM Exposure*Interest	-0.011*	0.007	-0.011*	0.007
Teacher Expectation*Interest	0.008	0.007	0.001	0.007
STEM Major ON				
Self-Efficacy	0.123***	0.007	0.063***	0.007
Outcome Expectation	0.058***	0.007	0.114***	0.007
STEM Occupation	0.145***	0.007	0.126***	0.007

Model Effects	Math		Science	
	β	SE	β	SE
Teacher Expectations	0.003	0.007	0.008	0.007
School Informal STEM Exposure	0.022***	0.007	0.023***	0.007
Teacher Beliefs	0.001	0.007	0.001	0.007
School Informal STEM Exposure*Occupation	-0.005	0.007	-0.003	0.007
Teacher Expectations*Occupation	0.006	0.007	0.000	0.007
Teacher Beliefs*Occupation	0.009	0.007	0.006	0.007

Note: $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***; Estimates are standardized

Summary of Research Question 2 Findings

Table 35 below presents a summary of findings for research question two. Hypotheses, results, and interpretations are presented.

Table 35. ***Summary of Research Question 2 Findings***

Hypotheses	Results for Math and Science Models	Interpretation
Learning Experiences		
Aptitude influences self-efficacy	Significant for math model Not applicable to science model	Students' past learning experiences were significant predictors of their self-efficacy and outcome expectation, thus an important aspect of their overall STEM career development.
Aptitude influences outcome expectation	Significant for both models	
Identity influences self-efficacy	Significant for both models	
Identity influences outcome expectation	Significant for both models	
Informal learning influences self-efficacy	Significant for both models	
Informal learning influences outcome expectation	Significant for both models	
Core SCCT Model		
Self-efficacy influences outcome expectation	Significant for both models	The core Social Cognitive Career Theory model significantly predicted students' STEM career intentions and STEM major selections. This was true for both the math and science models. Overall, SCCT's core model was predictive of students' STEM career development.
Self-efficacy influences interest	Significant for both models	
Outcome expectation influences interest	Significant for both models	
Self-efficacy influences intent to pursue STEM career	Significant for both models	

Outcome expectation influences intent to pursue STEM career	Significant for both models	
Interest influences intent to pursue STEM career	Significant for both models	
Self-efficacy influences STEM major selection	Significant for both models	
Outcome expectation influences STEM major selection	Significant for both models	
STEM career intention influences STEM major selection	Significant for both models	
Environmental Supports and Barriers		
Teacher beliefs influence students' intent to purse STEM career	Insignificant for both models	Environmental supports and barriers that existed within students' school environments were not fully predictive of students' STEM career intentions or STEM majors selections. They also did not moderate most hypothesized relationships. The most predictive environmental variable was informal STEM exposure, which significantly influenced students' STEM major selections.
Teacher expectations influence students' intent to purse STEM career	Significant only for math model	
School informal STEM exposure influences students' intent to purse STEM career	Insignificant for both models	
Teacher beliefs influence students' STEM major selection	Insignificant for both models	
Teacher expectations influence students' STEM major selection	Insignificant for both models	

School informal STEM exposure influences students' STEM major selection	Significant for both models
Teacher beliefs moderate the relationship between students' interests and intentions to pursue STEM careers	Significant only for science model
Teacher expectations moderate the relationship between students' interests and intentions to pursue STEM careers	Insignificant for both models
School informal STEM exposure moderates the relationship between students' interests and intentions to pursue STEM careers	Significant only for math model
Teacher beliefs moderate the relationship between students' intentions to pursue STEM careers and their selection of STEM majors	Insignificant for both models
Teacher expectations moderate the relationship between students' intentions to pursue STEM careers and their selection of STEM majors	Insignificant for both models
School informal STEM exposure moderates the relationship between students' intentions to pursue STEM careers and their selection of STEM majors	Insignificant for both models

Research Question 3

RQ 3: Are there differences in how math-related core Social Cognitive Career Theory predictors (i.e., math- self-efficacy, outcome expectation, and interest) influence STEM career intentions and major selection, based on gender, race/ethnicity, or socio-economic status?

To address research question 3, multiple analyses of the analytical model structure were conducted to identify potential similarities and differences in regression coefficients across groups. Each multi-group analysis, started with a baseline multi-group model, which compared each category within the associated subgroup (e.g., males and females within gender). Initially, all parameters were allowed to freely estimate. Then, all paths for which the regression coefficients were significant for all categories were identified. This was to test whether these coefficients were actually the same or statistically different across groups. A Chi-square difference test was conducted on the identified regression paths.

The Chi-square difference test entailed individually constraining each of the regression coefficients to be equal for the identified paths to examine if there were significant differences across groups. If the Chi-square difference test yielded a *p*-value less than 0.05, I rejected the null hypothesis, which hypothesizes that there is no difference in regression coefficients across groups (i.e., if the *p*-value was less than 0.05, this meant that the regression coefficients were statistically different). Conversely, if the *p*-value was greater than 0.05, then the null hypothesis was not rejected, indicating that there were no differences between groups (i.e., if the *p*-value was greater than 0.05, this meant that statistically, the regression coefficients were equal). Finally, all regression paths that were determined not to be statistically different across groups were constrained equal, meaning the regression coefficients would be the same for all. All other regression coefficients were allowed to freely estimate. This led to a more parsimonious final model. Table 36 below details the number of iterations of model refinement engaged to produce the final analytical model for each multi-group analysis.

Table 36. ***Analytical Model Structure for 3 Demographic Variables***

Subgroup	Initial Model	Models Tested	Final Model
Gender Male = 1, Female = 2	1	8[a]	1[d]
Race/ethnicity White = 1, Asian = 2, Black = 3, Latino = 4	1	4[b]	1[e]
Socio-economic Status Q1 = 1, Q2 = 2, Q3 = 3, Q4 = 4, Q5 = 5	1	4[c]	1[f]

Note: a = 8 regression coefficients that were significant for both genders; b = 4 regression coefficients that were significant across all racial/ethnic groups; c = 4 regression coefficients that were significant across all socio-economic quintiles; d = 3 regression coefficients are constrained equal across groups (see highlighted in Table 38); e = 3 regression coefficients are constrained equal across groups (see highlighted in Table 39); f = 2 regression coefficients are equal across groups (see highlighted in Table 40)

Core Math Model Fit Indices by Subgroup

The Core Math Model was analyzed by gendered, racial/ethnic, and socio-economic subgroups. Fit indices for each model suggested excellent model fit. The fit statistics for the gender-specific model were χ^2/df ratio = 3.262, CFI=0.997, and TLI = 0.990; χ^2/df ratio = 1.911, CFI = 0.997, and TLI = 0.992 for race/ethnicity; and χ^2/df ratio = 1.101, CFI = 0.999, and TLI = 0.998 for socio-economic status. See table below.

Table 37. ***Math Model Fit Indices by Subgroup***

	Overall Goodness of Fit and Fit Indices						
	Chi-square/df (ratio)		RMSEA			CFI/TLI	
Sub-groups	χ^2/df=(ratio)	*p* value	Estimate	90% CI	RMSEA <= .05	CFI	TLI
Gender	16.308/5	.006	.015	.007,	1.000	0.997	0.990

	(3.262)			.024			
Race/ethnicity	24.845/13 (1.911)	.024	.014	.005, .023	1.000	0.997	0.992
Socio-economic status	14.413/13 (1.101)	.345	.005	.000, .017	1.000	0.999	0.998

Core Math Model by Gender

In the baseline gender model, there were eight regression paths whose coefficients were significant for both male and female students. Thus, a Chi-square difference test was conducted on each of those eight regression paths. After testing for difference between groups on each regression, there were three that were found to be equal. These were path#5 (χ^2 (1)=0.055, p = 0.8152); path#6 (χ^2 (1)=3.120, p = 0.0774); and path#9 (χ^2 (1)=0.540, p = 0.4623). Therefore, these three regression coefficients were constrained equal in a final model. All others were allowed to estimate freely (i.e., regression coefficients on paths 1, 2, 3, 4, 7, and 8). The Chi-square difference test for the final model was χ^2 (5)=16.308, p = 0.0060).

Equality Across Gender

The regression paths from self-efficacy to intent to pursue a STEM career; outcome expectation to intent to pursue a STEM career; and self-efficacy to STEM major selection were constrained equal for both gendered groups. Chi-square difference testing concluded that the coefficients of each of the associated regression paths were equal for male and female students. Each of these regressions was positive and significant.

Gender Differences

All regressions in the model were positively significant for both male and female students, except one. While math outcome expectation significantly influenced STEM major selection for males, outcome expectation was not a significant predictor of STEM major selection for females. Otherwise, for both male and female students, self-efficacy was a significant predictor of outcome expectation; interest was positively and significantly influenced by self-efficacy and outcome expectation; self-efficacy, outcome expectation, and interest were significant predictors of intent to pursue a STEM career; and STEM major selection was significantly influenced by self-efficacy, and intent to pursue a STEM career.

The regression coefficients from self-efficacy to outcome expectation; self-efficacy to interest; outcome expectation to interest; interest to STEM career intentions; and STEM career intentions to STEM major selection displayed configural invariance, as they were all significant for both groups, but the strengths of association for each regression were different across gender. The influence of self-efficacy on interest was slightly stronger for females, but the influence of outcome expectation on interest was slightly weaker. Additionally, the association between self-efficacy and outcome expectation; interest and intent to pursue a STEM career; and intent to pursue a STEM career and STEM major selection were higher for male students than female students. Figure 7 below depicts the structural equation modeling of the core math model by gender. Additionally, Table 38 below presents the estimates of both models.

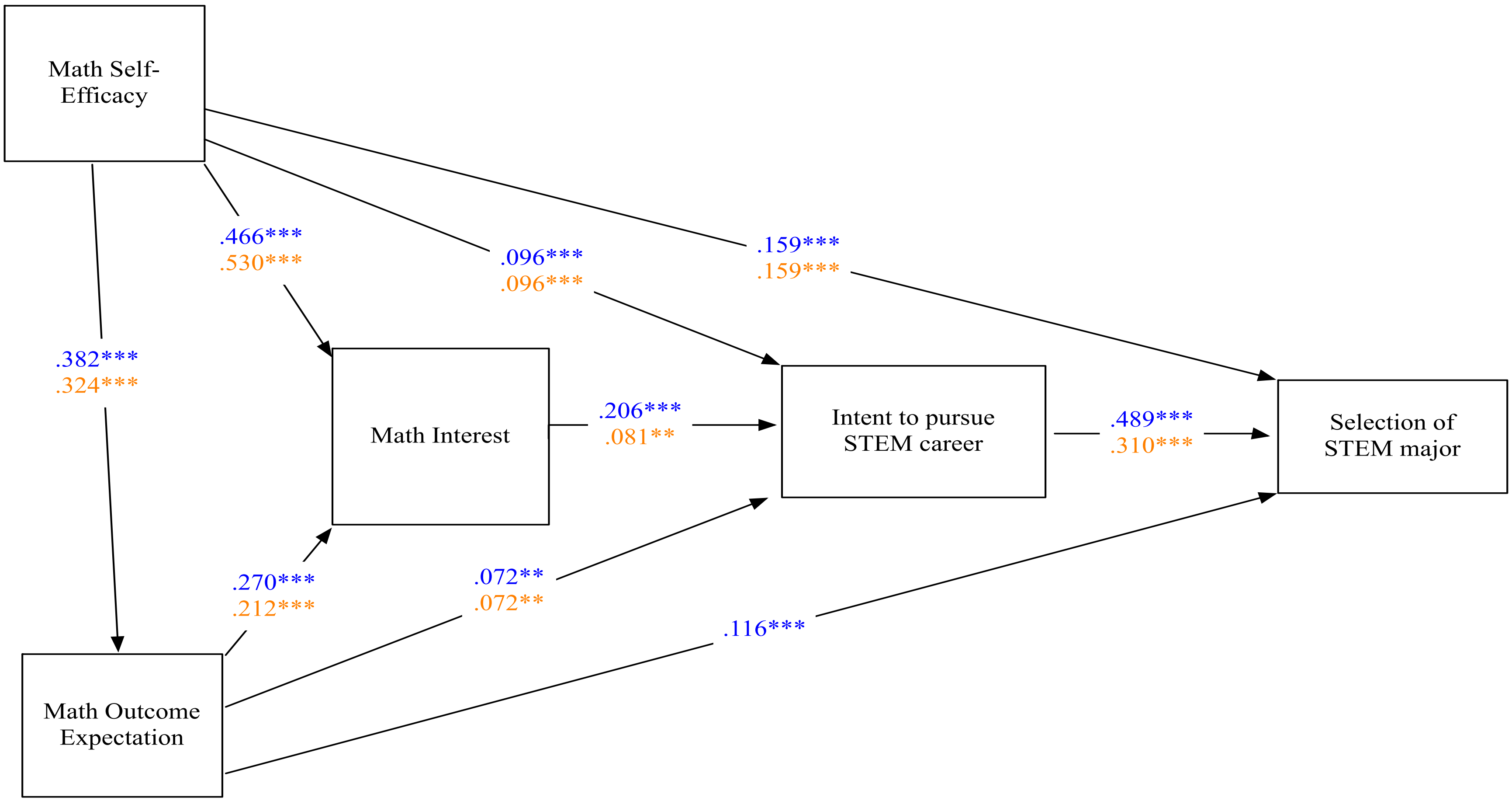


Figure 7. *Core Math Model by Gender*
Note: Blue parameters represent males, orange females; $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***; insignificant parameters omitted

Table 38. ***Estimates of Core Math Model by Gender***

Model Effects	Male			Female		
	β	β*	SE*	B	β*	SE*
Outcome Expectation ON						
Self-Efficacy	0.382***	0.374***	0.013	0.324***	0.332***	0.014
Interest ON						
Outcome Expectation	0.270***	0.262***	0.015	0.212***	0.209***	0.015
Self-Efficacy	0.466***	0.444***	0.014	0.530***	0.535***	0.011
STEM Occupation ON						
Interest	0.206***	0.201***	0.029	0.081**	0.079**	0.027
Outcome Expectation	0.072**	0.068**	0.020	0.072**	0.069**	0.021
Self-Efficacy	0.096***	0.089***	0020	0.096***	0.095***	0.021
STEM Major ON						
STEM Occupation	0.489***	0.437***	0.029	0.310***	0.294***	0.035
Outcome Expectation	0.116***	0.098***	0.027	0.060	0.055	0.035
Self-Efficacy	0.159***	0.132***	0.020	0.159***	0.149***	0.023

Note: β *, SE* are standardized estimates; *p* < .05 = *, *p* < .01 = **, and *p* < .001 = ***; highlighted are coefficients that are equal across groups.

<u>Core Math Model by Race/Ethnicity</u>

In the baseline racial/ethnic model, there were four regression paths whose coefficients were significant for all racial/ethnic groups. Thus, a Chi-square difference test was conducted on those four regression paths. After testing for difference between groups on each regression, there were three that were found to be equal. These were path#2 (χ^2 (3)=3.598, p = 0.3083); path#3 (χ^2 (3)=3.157, p = 0.3681); and path#7 (χ^2 (3)=4.610, p = 0.2027). Therefore, these three coefficients were constrained equal in a final model. All others were allowed to estimate freely (i.e., regression coefficients on paths 1, 4, 5, 6, 8, and 9). The chi-square difference test for the final model was χ^2 (9)=10.165, p = 0.3373).

Equality Across Racial/Ethnic Groups

The influence of both self-efficacy (0.484) and outcome expectation (0.256) on interest were equal across all racial/ethnic groups. Similarly, intent to pursue a STEM career was a positive, significant predictor of selection of a STEM major, with the relationship being equal across all groups (0.346). Racial/ethnic differences of significance for all other model regressions are described below.

White Student Subpopulation

In addition to the significant relationships that were equal across groups, self-efficacy was a significant, positive predictor of outcome expectation for White students. Additionally, while interest and outcome expectation were significant predictors of intent to pursue a STEM career, self-efficacy was not. Finally, self-efficacy and outcome expectation were both positive, significant predictors of STEM major selection. White students were the only group where outcome expectation was shown to be a significant predictor of STEM major selection.

Asian Student Subpopulation

In addition to the significant relationships that were equal across groups, self-efficacy was a significant, positive predictor of outcome expectation for Asian students. While interest and outcome expectation were significant predictors of intent to pursue a STEM career, self-efficacy was not. In terms of predicting STEM major selection, self-efficacy was a significant and positive influence, whereas outcome expectation was not.

Black Student Subpopulation

In addition to the significant relationships that were equal across groups, self-efficacy was a significant, positive predictor of outcome expectation for Black students. None of the proposed model constructs were found to be significant predictors of intent to pursue a STEM career, an anomaly only present with Black students. Intent to pursue a STEM career was the only significant influence on STEM major selection. This suggests that for Black students, self-efficacy and outcome expectation were not found to be significant predictors of STEM career pursuits (i.e., STEM career intentions and major selections).

Latino Student Subpopulation

In addition to the significant relationships that were equal across groups, self-efficacy was a significant, positive predictor of outcome expectation for Latino students. While interest and outcome expectation were not predictors of STEM career intentions, self-efficacy was shown to be a significant influence. In fact, Latino students are the only group where self-efficacy was found to be a significant influence on STEM career intentions.

Overall, the model seemed to best predict STEM career pursuit for White students. The model was also largely predictive of Asian students' STEM career pursuits, too. The model was moderately successful at predicting Latino students' STEM career pursuits. Overwhelmingly, the model was least predictive for Black students. Figure 8 below displays all significant paths for each racial/ethnic group. Additionally, Table 39 provides information regarding all model estimates.

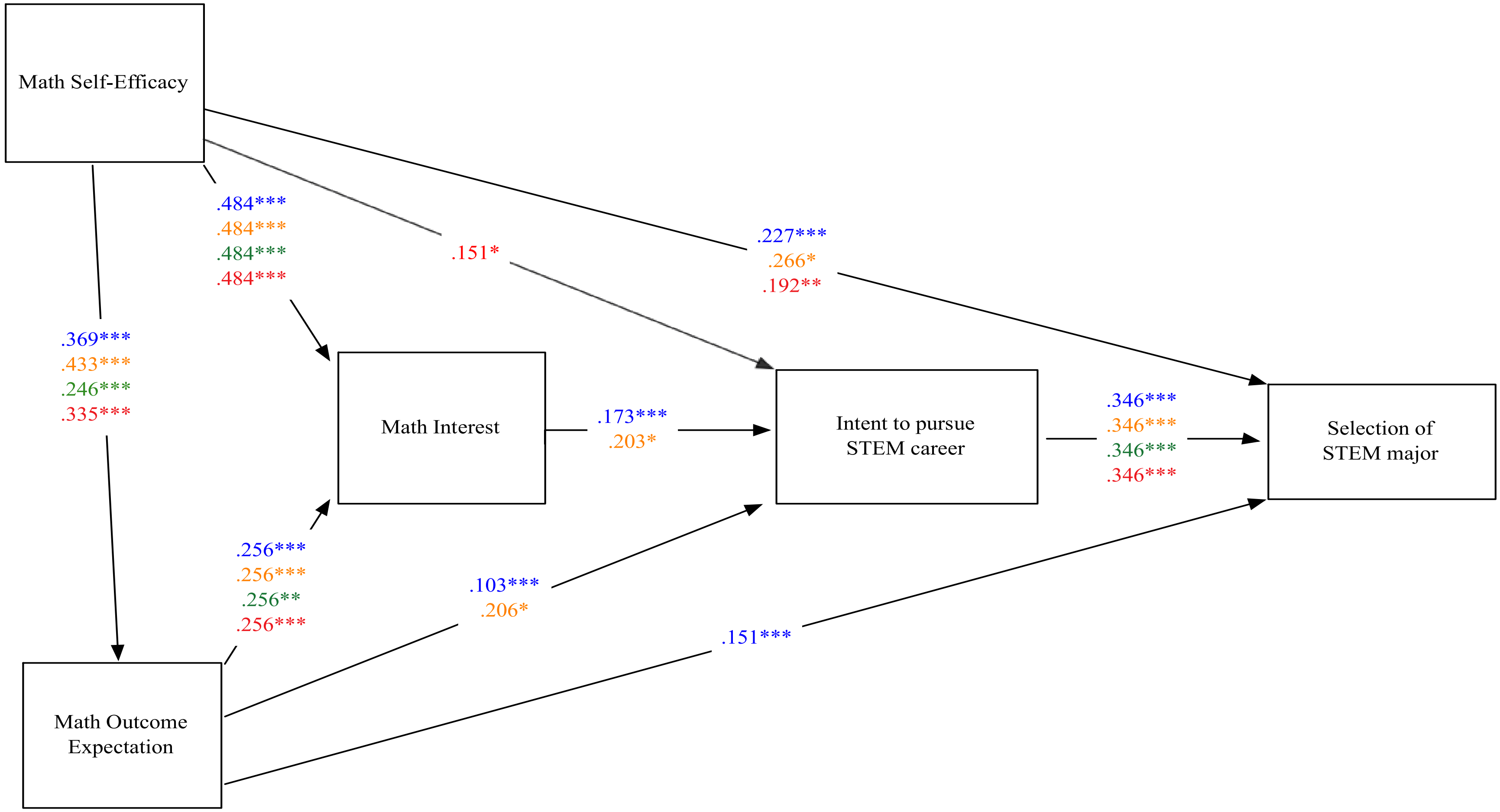


Figure 8. ***Core Math Model by Race/ethnicity***

Note: Blue parameters represent White, orange Asian, green Black, and red Latino; $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***, insignificant parameters omitted.

Table 39. ***Estimates of Core Math Model by Race/Ethnicity***

	White			Asian			Black			Latino		
Model Effects	β	β*	SE*	B	β*	SE*	B	β*	SE*	β	β*	SE*
Outcome Expectation ON												
Self-Efficacy	0.369***	0.376***	0.011	0.433***	0.410***	0.039	0.246***	0.254***	0.034	0.335***	0.325***	0.029
Interest ON												
Outcome Expectation	0.256***	0.249***	0.010	0.256***	0.261***	0.015	0.256***	0.243***	0.012	0.256***	0.255***	0.011
Self-Efficacy	0.484***	0.481***	0.009	0.484***	0.469***	0.016	0.484***	0.476***	0.016	0.484***	0.468***	0.013
STEM Occupation ON												
Interest	0.173***	0.170***	0.024	0.203*	0.180*	0.076	0.090	0.091	0.071	0.094	0.089	0.064
Outcome Expectation	0.103***	0.099***	0.020	0.206**	0.187**	0.072	-0.022	- 0.021	0.054	0.023	0.022	0.061
Self-Efficacy	0.039	0.038	0.022	0.118	0.102	0.069	-0.004	-0.004	0.065	0.151*	0.138*	0.054
STEM Major ON												
STEM Occupation	0.346***	0.317***	0.022	0.346***	0.341***	0.026	0.346**	0.327***	0.023	0.346***	0.320***	0.023
Outcome Expectation	0.151***	0.132***	0.023	-0.169	-0.155	0.090	-0.078	-0.070	0.078	0.143	0.124	0.069
Self-Efficacy	0.227***	0.203***	0.024	0.266**	0.225**	0.080	0.078	0.073	0.079	0.192**	0.162**	0.055

Note: β *, SE* are standardized estimates; $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***; highlighted are coefficients that are equal across groups.

<u>Core Math Model by Socio-economic Status</u>

In the baseline socio-economic model, there were four regression paths whose coefficients were significant across all five quintiles. Thus, a Chi-square difference test was conducted on those four regression paths. After testing for difference between groups on each regression, there were two that were found to be equal. These were path#3 (χ^2 (4)=3.133, p = 0.5358) and path#7 (χ^2 (4)=4.581, p = 0.3331). Therefore, these two regression coefficients were constrained equal in a final model. All others were allowed to estimate freely (i.e., regression coefficients on paths 1, 2, 4, 5, 6, 8, and 9). The Chi-square difference test for the final model was χ^2 (8)=7.880, p = 0.4452).

Equality Across Racial/Ethnic Groups

The influence of self-efficacy (0.481) on interest was equal across all socio-economic groups. Similarly, intent to pursue a STEM career was a positive, significant predictor of selection of a STEM major, with the relationship being equal across all groups (0.381). Socio-economic differences of significance for all other model regressions are described below.

Lowest Socio-economic Quintile

In addition to the relationships that were equal across groups, for student in the lowest socio-economic quintile, self-efficacy was a significant, positive predictor of outcome expectation. Additionally, interest was significantly and positively influenced by outcome expectation. Only self-efficacy was found to be a significant influence on STEM career intentions. Finally, STEM major selection was significantly and positively influenced by self-efficacy.

Second Socio-economic Quintile

In addition to the relationships that were equal across groups, for students in the second socio-economic quintile, self-efficacy was a significant, positive predictor of outcome expectation. Additionally, interest was significantly and positively influenced by outcome expectation. Of the hypothesized predictors of STEM career intentions, only interest was shown to be significant. STEM major selection was significantly and positively influenced by outcome expectation, but not self-efficacy. In fact, students in the second quintile were the only group where self-efficacy was shown not to be a significant predictor of STEM major selection.

Third Socio-economic Quintile

In addition to the relationships that were equal across groups, for students in the third socio-economic quintile, self-efficacy was a significant, positive predictor of outcome expectation. Additionally, interest was significantly and positively influenced by outcome expectation. None of the hypothesized predictors of STEM career intentions were significant influences. Finally, self-efficacy was a significant influence on STEM major selection, but outcome expectation was not.

Fourth Socio-economic Quintile

Similar to all other groups, in addition to the relationships that were equal across groups, self-efficacy was a significant, positive predictor of outcome expectation. Additionally, interest was significantly and positively influenced by outcome expectation. Only interest was shown to be a significant predictor of intent to pursue a STEM career. In addition, both self-efficacy and outcome expectation were positive, significant influences on STEM major selection, with STEM career intentions being the strongest of the two.

Highest Socio-economic Quintile

The Core SCCT model was most successful in terms of predicting students' STEM career intentions and STEM major selections for students in the highest socio-economic quintile. All direct paths, except the direct path from self-efficacy to STEM career pursuit intentions were significant. In fact, self-efficacy was shown to only be a significant predictor of intent to pursue a STEM career for students in the lowest socio-economic group. Figure 9 below displays all significant paths for each socio-economic quintile. Additionally, Table 40 provides information regarding all model estimates.

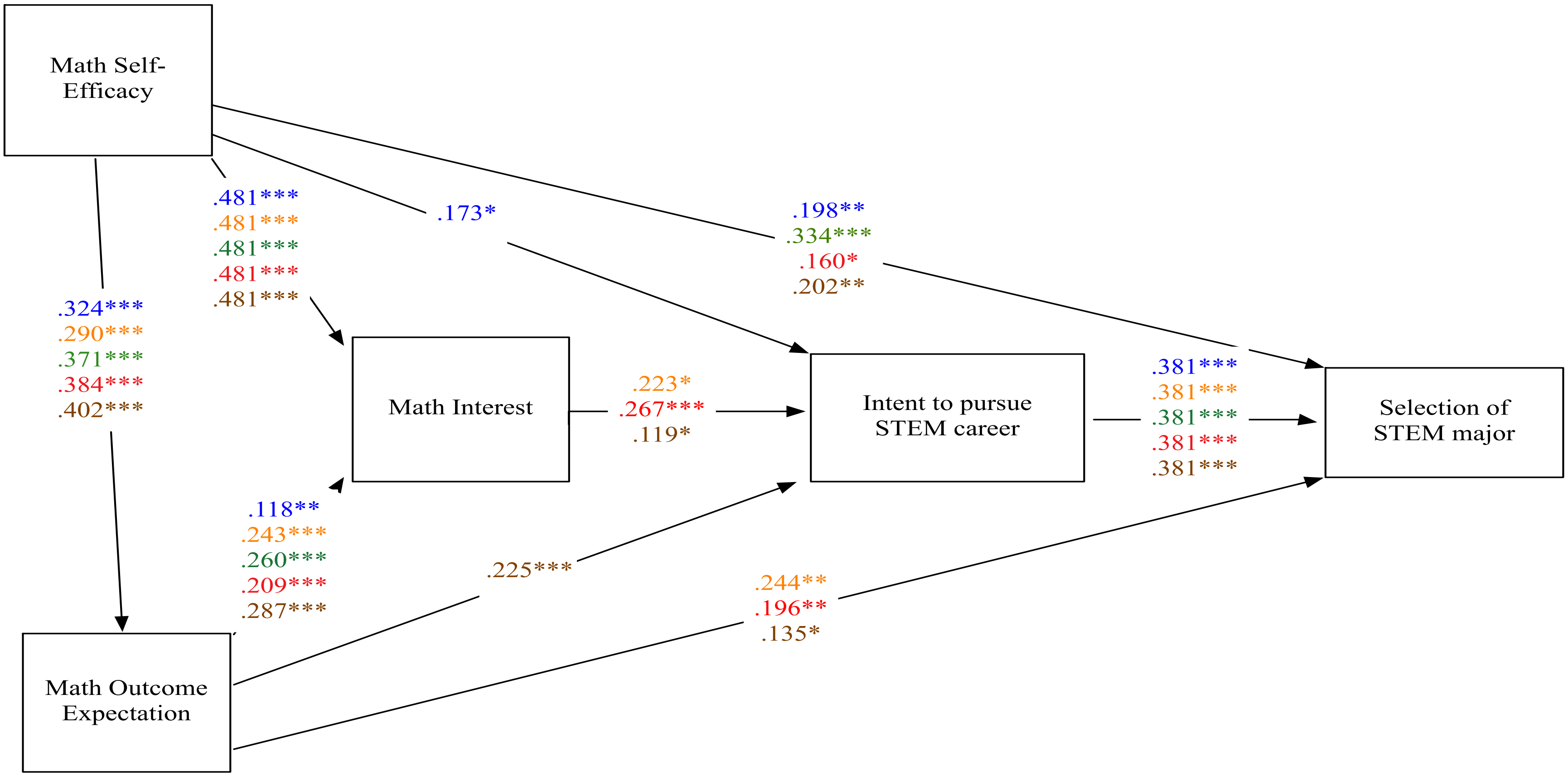


Figure 9. ***Core Math by Socio-economic Status***
Note: Blue parameters represent the lowest SES quintile, orange second, green third, red fourth, and brown highest; $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***, insignificant parameters omitted; insignificant paths grey.

Table 40. ***Estimates of Core Math Model by Socio-economic Status***

	Lowest		2nd Quintile		3rd Quintile		4th Quintile		Highest	
Model Effects	B	SE	B	SE	β	SE	β	SE	β	SE
Outcome Expectation ON										
Self-Efficacy	0.324***	0.034	0.290***	0.036	0.371***	0.032	0.384***	0.028	0.402***	0.027
Interest ON										
Outcome Expectation	0.118**	0.036	0.243***	0.038	0.260***	0.032	0.209***	0.028	0.287***	0.024
Self-Efficacy	0.481***	0.016	0.481***	0.016	0.481***	0.016	0.481***	0.016	0.481***	0.016
STEM Occupation ON										
Interest	0.052	0.080	0.223**	0.076	0.058	0.084	0.267***	0.073	0.119*	0.051
Outcome Expectation	0.009	0.077	0.088	0.062	0.087	0.060	0.045	0.056	0.225***	0.048
Self-Efficacy	0.173*	0.072	0.004	0.066	0.065	0.068	-0.019	0.065	-0.006	0.051
STEM Major ON										
STEM Occupation	0.381***	0.039	0.381***	0.039	0.381***	0.039	0.381***	0.039	0.381***	0.039
Outcome Expectation	-0.061	0.096	0.244*	0.108	0.051	0.096	0.196**	0.073	0.135*	0.059
Self-Efficacy	0.199	0.103	0.041	0.094	0.334***	0.094	0.160*	0.067	0.202**	0.062

Note: $p < .05$ = *, $p < .01$ = **, and $p < .001$ = ***; highlighted are coefficients that are equal across groups.

Summary of Research Question 3 Findings

Table 41 below presents a summary of findings for research question three. Hypotheses, results, and interpretations are presented.

Table 41. ***Summary of Research Question 3 Findings***

Hypotheses	Results Model	Interpretation
Gender Model		
Self-efficacy influences outcome expectation	Significant for both genders	The core Social Cognitive Career Theory model significantly predicted students' STEM career intentions and STEM major selections. This was true for both male and female students. Overall, SCCT's core model was predictive of students' STEM career development when examining STEM career development by gender.
Self-efficacy influences interest	Significant for both gender	
Outcome expectation influences interest	Significant for both genders	
Self-efficacy influences intent to pursue STEM career	Significant for both genders	
Outcome expectation influences intent to pursue STEM career	Significant for both genders	
Interest influences intent to pursue STEM career	Significant for both genders	
Self-efficacy influences STEM major selection	Significant for both genders	
Outcome expectation influences STEM major selection	Significant for males Insignificant for females	
STEM career intention influences STEM major selection	Significant for both genders	
Race/ethnicity Model		

Table 41. ***Summary of Research Question 3 Findings***

Hypotheses	Results Model	Interpretation
Self-efficacy influences outcome expectation	Significant for all groups	The Social Cognitive Career Theory core model seemed to best predict STEM career pursuit for White students. The model was also largely predictive of Asian students' STEM career pursuits. The model was moderately successful at predicting Latino students' STEM career pursuits. Overwhelmingly, the model was least predictive for Black students.
Self-efficacy influences interest	Significant for all groups	
Outcome expectation influences interest	Significant for all groups	
Self-efficacy influences intent to pursue STEM career	Significant only for Latino students	
Outcome expectation influences intent to pursue STEM career	Significant for White and Asian students	
Interest influences intent to pursue STEM career	Significant for White and Asian students	
Self-efficacy influences STEM major selection	Significant for White, Asian, and Latino students	
Outcome expectation influences STEM major selection	Significant for only for White students	
STEM career intention influences STEM major selection	Significant for all groups	
Socio-economic Model		
Self-efficacy influences outcome expectation	Significant for all groups	The Social Cognitive Career Theory core model seemed to best predict STEM career pursuit for students in the highest socio-economic quintile. The model was
Self-efficacy influences interest	Significant for all groups	

Table 41. ***Summary of Research Question 3 Findings***

Hypotheses	Results Model	Interpretation
Outcome expectation influences interest	Significant for all groups	also largely predictive of students in the fourth quintile's STEM career pursuits. The model was moderately successful at predicting students in the lowest two quintiles' STEM career pursuits. Overwhelmingly, the model was least predictive for students in the 3^{rd} quintile.
Self-efficacy influences intent to pursue STEM career	Significant only for the lowest quintile	
Outcome expectation influences intent to pursue STEM career	Significant only for the highest quintile	
Interest influences intent to pursue STEM career	Significant for highest, 4^{th}, and 2^{nd} quintiles	
Self-efficacy influences STEM major selection	Significant for highest, 4^{th}, 3^{rd}, and lowest quintiles	
Outcome expectation influences STEM major selection	Significant for highest, 4^{th}, and 2^{nd} quintile	
STEM career intention influences STEM major selection	Significant for all groups	

As demonstrated in the table above, the proposed Core Math Model, based in Social Cognitive Career Theory, resulted in different levels of predictability, which depended heavily on subgroup. The model displayed very minute gender differences, and was overall highly predictive of STEM career development for both male and female students. Conversely, the model's predictability varied more substantially when examined by students' race/ethnicity and socio-economic status. The model most successfully predicted STEM-oriented career behaviors of White and Asian students, and those in the highest two socio-economic quintiles. The model was moderately predictive for Latino students, and those in the lowest two socio-economic quintiles. The model was least predictive for Black students, and those in the third socio-economic quintile.

STEM career intention was hardest to predict. Across race and socio-economic status, interest proved to be a stronger, more significant predictor of students' STEM career intentions than self-efficacy and outcome expectation. Similarly, outcome expectation was least predictive of STEM major selection for females, as well as many racial/ethnic and socio-economic subgroups. Overall, these findings suggest that Social Cognitive Career Theory can be highly predictive of STEM career development for some groups (e.g., Whites, Asians, males, those with high socio-economic status), but other career theory frameworks may be more appropriate for others.

Summary of Chapter 4 Findings

This research examined the STEM career development process of high school students. Data were derived from High School Longitudinal Study of 2009, a nationally representative, longitudinal dataset. Nearly 24,000 high school students from diverse gendered, racial/ethnic, and socio-economic backgrounds were included in this study.

Students attended more than 944 high schools, which were comprised of both public and private institutions, and were located within different locales and geographical regions across the country. Key variables analyzed included students' math and science- self-efficacy, outcome expectation, and interest; STEM career intentions; and STEM major selections. Contextual variables analyzed included students' math aptitude, math and science identity, and informal STEM participation. Additionally, math and science teachers' beliefs and expectations and school informal STEM exposure were examined.

Combined, findings presented in Chapter 4 suggest that there are many differences in STEM-oriented dispositions, behaviors, career and academic pursuits, and overall career development processes based on an individual's gender, race/ethnicity, and socio-economic status. Many of these differences become even more robust when examining STEM career development by the intersection among identity categories.

Female students intended to pursue STEM at higher rates than male students, and were more drawn to health occupations. Male students were more drawn to life and physical sciences, engineering, mathematics, and information technology careers. Asians had the highest percentage of students with STEM career intentions, followed by Black, White, and Latino students. Across race, students were most drawn to health occupations. However, when examining life and physical sciences, engineering, mathematics, and information technology career intentions, Asians and Whites were slightly over-represented and Blacks and Latinos were slightly under-represented. Additionally, STEM career intentions increased with socio-economic status. Again, across socio-economic status, students intended to pursue health careers most. However, when considering life and physical sciences, engineering, mathematics, and information technology, students in the highest socio-economic quintile were nearly twice as likely as those in all other quintiles to want to pursue this sub-domain.

Examining STEM major intentions, male students intended to select STEM majors in college at higher percentages than female students. Additionally, Asian and White students had intentions of selecting STEM majors at higher rates than Blacks and Latinos. Finally, STEM major selection increased with students' socio-economic status.

Finally, while the entire contextual model was highly predictive of STEM career behaviors for high school students overall (with the exception of environmental supports and barriers), examination of STEM career development by race/ethnicity, gender, and socio-economic status highlighted group differences. Students' STEM career development substantially differed based on their identity categories, as indicated by the varied predictability of the proposed Core Math Model. Chapter 5 will discuss the implications of each of these findings.

Chapter 5: Discussion and Conclusion

This research examined high school students' STEM career development using a Social Cognitive Career Theory framework. A discussion of findings of this study will be presented in this chapter. The discussion starts with an overview of student demographics. Next, the discussion moves to an overview of student learning experiences and how understandings were enlightened when exploring these phenomena from an intersectional lens. The discussion then shifts to address the study's research questions. Following a discussion of research findings, challenges, limitations, and strengths of this study; implications for instructional design and the STEM workforce; suggestions for future research; and final conclusions are presented.

Demographics, Education, Intersectionality, and Disparity

The data were very telling of the demographic distribution of the sub-populations of high school students who participated in this longitudinal study. There are disparities across groups (e.g., race, gender, socio-economic status), and on many levels (e.g., race intersected with socio-economic status). When examining students' race/ethnicity, gender, and socio-economic status as separate demographic categories, the study's population distributions were as expected, and consistent with that of the greater American public. However, when considering the intersection among students' identity categories, disparities become apparent. Compared with their representation in the population, Blacks and Latinos were over-represented in the lowest socio-economic quintiles, while Whites and Asians were over-represented in the highest. The implication, especially with regard to STEM, can be significant.

Race is a socially constructed phenomenon; however, one can argue that an individual's socio-economic status can provide insight into the educational limitations and affordances being experienced (American Psychological Association, n.d.). Children from low socio-economic backgrounds develop academic skills slower than their higher socio-economic counterparts (Morgan, Farkas, Hillemeier, & Maczuga, 2009). Moreover, children from higher socio-economic backgrounds are more likely to achieve proficiency on math tasks (Coley, 2002). Schools in low socio-economic communities are typically under-resourced, which further inhibits academic progress (Aikens & Barbarin, 2008). Teacher qualification is positively linked to teacher success and student achievement (Akiba, LeTendre, & Scribner, 2007; Powers, 2003), however, teacher qualifications are often lower in high poverty classrooms (Wang, 2013).

In the data investigated in this study, only about one-fourth of Black students, and less than 22 percent of Latino students, were in the highest two socio-economic quintiles. Conversely, nearly 53 percent of White students and 57 percent of Asian students occupied those same quintiles. Additionally, while 29 percent of White students and 18 percent of Asian students were in the lowest two socio-economic quintiles, more than 54 percent of Black students and nearly 65 percent of Latino students occupied that same demographic. This suggests that Black and Latino students are more likely to live in low-income communities, whose schools are under-resourced. Thus, Black and Latino students are more likely to encounter academic challenges associated with coming from low socio-economic backgrounds, whereas Asian and White students are more like to achieve higher academic proficiency, especially with regard to math.

Reflecting on the conditions of schools within low socio-economic communities and the implications that result, coupled with the racial/ethnic groups primarily serviced by these institutions, it becomes clear how racial disparities in education continue to transpire. Ethnic minorities and individuals from low socio-economic backgrounds are more likely to receive training from less qualified teachers, and thus are less likely to have the competence, preparation, and skills required for advanced math and science courses needed to succeed in STEM (Wang, 2013). STEM subjects already pose difficulties for most learners (Fuchs, Compton, Fuchs, Paulsen, Bryant, & Hamlett, 2005), even in absence of barriers relating to educational resources (Aiken & Barbarin, 2008) and teacher quality (Ingersoll, 1999).

These assertions are supported by this study’s results, as Black and Latino students performed lowest on the math aptitude test, whereas Asians and Whites achieved relatively high math aptitude scores. Discussions surrounding the under-representation of particular racial minorities (e.g., Blacks, Latinos, and Native Americans) within STEM must also recognize that an individual has multiple identities that are always acting in tandem. For example, this is demonstrated in findings from this study, as Black female students in the highest socio-economic quintile outperformed nearly all other groups on the math aptitude test, despite Black students on average having the lowest math aptitude scores. This supports the idea that it is time to extend the dialogue to reflect these complex intersections as STEM development is further pushed in educational contexts.

Learning Experiences

Math Aptitude

Consistent with prior research, using the national dataset, this investigation has shown that there continue to be differences in students' mathematical aptitude based on race and socio-economic status. Asian students had the highest math performance, followed by White students, Latino students, and Black students. Similarly, math performance increased with socio-economic levels. Taking an intersectional perspective, there were measureable differences across race when considering socio-economic status. For instance, Black students in the lowest socio-economic quintile were the lowest performing students overall. Even more eye opening was the gap that existed between the highest and lowest socio-economic quintiles within race. There was a considerable difference between the math performance of Black females in the lowest socio-economic quintile (M = 51.9) and those in the highest (M = 71.5). In this example, it seems that socio-economic status had a larger impact on student performance than students' 'Blackness.' This means that Black female students' socio-economic status was a stronger predictor of math aptitude than their race/ethnicity or gender. Again, Black females in the highest socio-economic group performed better than all other students, except other females in that same SES quintile and Asian males in the 3rd and highest quintiles. Though the literature suggests that Black students are the lowest performing group (Martin, 2009), when socio-economic status is introduced, as demonstrated in this research, the narrative can shift.

Inconsistent with the literature, however, were male and female student performances being nearly identical when comparing gender alone. Even more of an anomaly was that within each quintile (except the third), and across all races, female students outperformed males students, which contradicts normative rhetoric surrounding math performance and gender (Hyde, Lindberg, Linn, Ellis, & Williams, 2008).

Potential rationale is that stereotypes perpetuating the idea that females lack mathematical ability may actually distort reality (Shapiro & Williams, 2012; Wang, 2013). Research suggests that teachers often underestimate the math ability of females relative to males (Frome & Eccles, 1998). Further, female students are more likely than male students to suffer the consequences of low teacher expectations in math and science (McKown & Weinstein, 2002; Wang, 2012). However, an analysis of the math performance of over seven million students on state assessments indicated that there was not a gender difference that favored males, even when examining gender differences across race (Hyde, Lindberg, Linn, Ellis, & Williams, 2008). The data from this study supports this notion; across all racial/ethnic groups and socio-economic quintiles (except the third), female students outperformed their male counterparts on the math aptitude test. Comparing trends from the past to those of recent decades, cultural shifts may have impacted the nature of math performance as situated within the context of gender (Hyde et al., 2008). These include happenings like increases in math-course taking and other math-related experiences for females (Meece, Parsons, Kaczala, & Goff, 1982), thus potentially calling for new perspectives on gendered differences in math ability. Data from this study supports this position. Female students participated in informal math and science experiences at higher percentages than male students, indicating a cultural shift, and thus negating the idea that female students participate in STEM activities at lesser rates than their male peers.

Math Identity

In this study, male students' math identities were above average, while females students' math identity were below average. Similarly, Asian and Black student identities were above average, while Latinos' math identities were below average. White students' math identities were exactly on average. Asian students' math identity was two-fifths of a standard deviation above the mean. Math identities of Black and White student were closest.

Considering Black students had the lowest math aptitude, one would speculate that they would also have the lowest math identity, but that is not the case. Some might suggest that one's mathematics identity can be a reflection of more than ability, (e.g., sense of belonging, others' perceptions of your ability) (Martin, 2009). Others might argue that some students may have exaggerated math-related self-perceptions, which can be a product of school environmental contexts (e.g., grade inflation, low proficiency expectations) (Segal, 2014). In either case, heightened math identity can be leveraged—and further developed through support—to facilitate mathematics participation

(Anderson, 2007), which is key, as mathematics is a gateway to educational and economic opportunities (D'Ambrosio, 1990).

Data from this study identify a disparity between math aptitude and identity. While math aptitude is essential to future STEM success, a heightened sense of identity is equally important (Martin, 2009), especially with regard to making the decision to pursue STEM. Essentially, strength in both would be ideal, as it would increase the prospect of STEM participation (Wang, 2013). Thus, the goal is not to lessen Black students' (or any other demographic for that matter) math identity to match that of their aptitude. Instead, efforts should be taken to maintain or increase positive math identities among students, while simultaneously building competency in math ability. One such mechanism could be informal STEM learning, which is discussed below.

Informal Learning Participation

There were differences identified in students' informal STEM participation. For instance, female students participated in informal math and science learning activities at higher rates than male students. Similarly, Asian students participated in informal learning experiences at much higher percentages than other racial ethnic groups, with White students on average participating in informal learning the least. Finally, on average, students in the highest socio-economic quintiles participated in informal math and science learning experiences more than those in other quintiles, especially with regard to camps, competitions, and summer programs. While it is unknown what caused certain populations to engage in informal STEM learning and others to not, speculation could be made that informal STEM participation could have derived from students' interest in pursuing STEM occupations. There is consistency between findings regarding

STEM career intentions and STEM informal learning participation; that is, subpopulations of students who had the highest percentages of individuals intending to pursue STEM occupations also participated in informal STEM learning at the highest rates.

This study found that the informal learning activities engaged in by most students were study groups and tutoring for both math and science. The question becomes, was participation in these activities required remediation, or did students voluntarily seek out these avenues? Furthermore, was the purpose of participation to remedy deficiencies in baseline competency or were students striving to supplement and/or further enhance their understanding beyond standard requirements? Further investigations are necessary to identify the *whys* (e.g., purposes) for participation in study groups and tutoring. Other forms of informal learning that were investigated were clubs, competitions and summer programs. Although participating in study groups and tutoring can enhance math or science performance, they do not provide the same levels of exposure and experience as clubs, competitions, and summer programs. The data from this investigation suggested that students participated less in these types of informal learning experiences.

The significance of the types of information learning experiences engaged can be related to the goals of students who participate in them. Differences in levels of math or science self-efficacy, outcome expectation, or interest can exist between students trying to build basic skills compared with those seeking mastery. Those who are forced to partake in these types of services may not engage at the same level as those who sought out these opportunities on their own accord. Students whose main source of informal learning was involvement in tutoring and study groups compared to those who had participated in summer programs, clubs, and competitions may be different based on the individuals' personal interests and goals. These types of inquiries might shed light into how (e.g., required or sought after) students' involvement in various types of informal learning experiences may influence their future STEM participation. The questions become, which are most helpful to students who are seeking mastery and how can such informal learning experiences be 'marketed' to students who may have latent or not-yet-developed interests in STEM careers.

Core STEM Career Development Components

With the exceptions of math interest and science outcome expectation (where means were equal for both groups), male students had higher levels of math and science self-efficacy, outcome expectation, and interest than female students. Situating math-related self-efficacy, outcome expectation, and interest within the context of math aptitude, it be would expected for the reverse to be true. Normally, one might conclude that performance influences beliefs, where higher performances correlate to higher beliefs. This was the case for Asian students and those in the highest socio-economic quintile. Both groups were always among the highest performers on the math aptitude test, and also reported relatively high levels of self-efficacy, outcome expectation, and interest. However, female students performed higher than their male counterparts on the math aptitude test, but male students' math beliefs were always higher. This also held true when looking at Black students' beliefs; their beliefs were always among the highest, but their math performance was typically among the lowest. Conversely, White students' beliefs were among the lowest, but their math performance was among the highest.

We need to explore what contributes to an individual's math and science self-perceptions to better understand the nature of the relationships that exist. If not past performance, then what contributes most to students' development of positive self-efficacy beliefs, outcome expectations, or interests? Are conditions of the environment, stereotypes, or outside perceptions stronger influences than performance? Or, could it be the case that some students have inflated self-perceptions (DeAngelis, 2003; Chevalier et al., 2009), while others internalize doubt (van Aalderen-Smeets & van der Molen, 2016)? Further, are the anomalies that have been described above due to issues relating to normative comparisons of beliefs? Essentially, rather than comparing beliefs across groups, would it be more meaningful and/or insightful to examine student beliefs and perceptions relative to their personal growth? While possible, this claim should be evaluated in future research, as it is common practice to conduct between group comparisons within the literature (Hackett & Bentz, 1981; Wang, 2013; and Andersen & Ward, 2014).

These are questions that I am left contemplating after identifying what I perceive to be anomalies. For instance, female, Black, and Latino students had some of the highest intentions of pursuing STEM careers, but then were among the lowest in terms of STEM major selection. While these groups' STEM career intentions contradicted normative discourse regarding career-related STEM participation (Landivar, 2013), their STEM major selection was consistent with prior research findings (Wang, 2013). Additionally, Black students had some of the highest math and science self-percepts, but were among the lowest performing groups on the mathematics aptitude test.

Discovery of these complex phenomena could be highlighting potential flaws in approaches engaged during the examination of these constructs (e.g., between group differences versus within group change) and/or in the interpretation of what these findings actually represent, though approaches employed in this study are consistent with methodological practices of prior research engaged (Hackett & Betz, 1992; Wang, 2013). Perhaps, however, we can extend research approaches to include examinations of within-group change, especially when the longitudinal data are available (Landivar, 2013).

Research Question 1

Are there differences in STEM career intentions or STEM major selections, based on race/ethnicity, gender, or socio-economic status?

STEM Career Intentions

Nearly 35 percent of students intended to pursue some branch of STEM, which encompassed disciplines traditionally inclusive to these fields, (i.e., life and physical sciences, engineering, mathematics, and information technology), and those specific to the medical sciences (i.e., health-related occupations). Students were more than 2.5 times as likely to intend to pursue health occupations than occupations in life and physical sciences, engineering, mathematics, and information technology. However, the sciences and mathematics will likely be core to students' health education and training, as math and science are the foundation of STEM (Patton, 2013).

There were differences identified in students' STEM career pursuits by gender, race/ethnicity, and socio-economic status. Female students were more than 1.5 times as likely than male students to pursue STEM careers. However, female students were more drawn to health occupations, while male students were more inclined to pursue life and physical sciences, engineering, mathematics, and information technology. In fact, males were three times as likely than females to intend to pursue occupations in life and physical sciences, engineering, mathematics, and information technology, which is consistent with statistics on current STEM college and workforce trends (Landivar, 2013). The reverse held true for female students. Another perspective of the data can be gained by looking at STEM career development through race.

With regard to race, while there were small differences identified in students' STEM career pursuits, there were many consistencies in terms of the percentage of students within each racial/ethnic subgroup who intended to pursue STEM and the specific STEM subdomains students were most drawn to. White, Black, and Latino students intended to pursue STEM at nearly the same percentage (32-35 percent), but the percentage of Asian students with STEM career intentions was slightly higher (40 percent). Consistent with the overall population, within each racial/ethnic subgroup, more students intended to pursue health occupations than occupations in life and physical sciences, engineering, mathematics, and information technology. Comparing across race/ethnicity, students' representation within each subdomain was also fairly close to their representation in the larger population, with Whites and Asians slightly over-represented in life and physical science, engineering, and mathematics, and Whites and Latinos slightly under-represented in health occupations. Overall, these findings suggest that we may need to find ways to entice students to participate in life and physical sciences, engineering, mathematics, and information technology, as this subdomain of STEM is least pursued. Another critical lens of STEM career pursuits, in addition to gender and race, is through socio-economic status.

Analysis of socio-economic status was consistent with prior findings; students tended to select health occupations more than life and physical sciences, engineering, mathematics, and information technology. The distributions across socio-economic quintiles of students intending to pursue health occupations were similar to that of the population distribution. However, differences were identified when examining life and physical sciences, engineering, mathematics, and information technology career intentions across socio-economic quintiles. Students in the highest socio-economic quintile were nearly twice more likely than those in the lowest quintile to report that they intended to select an occupation in this sub-domain. This suggests that there are disparities with regard to participation in life and physical sciences, engineering, mathematics, and information technology, where males, Asians, Whites, and individuals of high socio-economic status are substantially more likely than other subgroups to pursue this STEM domain. We need to identity the source of these disparities so that we can begin to achieve more equitable STEM representation.

Each of these individual identity category analyses (i.e., gender, race/ethnicity, socio-economic status) is telling its own story, but does not truly represent the full *makeup* of the individual students. While largely consistent with analyses of students' individual identity categories, intersectional analysis yielded a more detailed description of student contexts and STEM career development. For instance, all males in the highest socio-economic quintile intended to pursue STEM careers in life and physical sciences, engineering, mathematics, and information technology at the highest percentages, except Asian males. Intersectional approaches helped to identify the smallest of nuances, and thus provided a more in-depth understanding of students' STEM career behaviors.

Overall, these findings suggest that student intentions of pursuing STEM occupations are there. Discussions often center the need to increase the participation of Black, Latino, and female students within STEM, as they remain underrepresented. Additionally, a large body of research suggests that these students may not have an interest in the STEM disciplines (Gunderson, Ramirez, Levine, & Beilock, 2012). However, this research shows that their interest indeed exists, and at a level similar to their counterparts. In fact, in the intersectional analysis, when comparing across race and gender, Black and female students had the highest within group percentages of students with STEM career intentions.

Supporting students' continued STEM career development could be accomplished by facilitating increased cultivation of these career aspirations, as high school occupational aspirations have been found to be predictive of college major selection (Ferriman, Lubinski, & Benhow, 2009; Wang & Degol, 2013). Understanding the factors that may be affecting students' decisions, goals, and pursuits may aid in nurturing these career intentions in our classrooms and communities (Wang & Degol, 2013). Further, leveraging students' STEM career intentions that have already begun to develop could help to transform them from possibilities to realizations. If we create the mechanisms that allow for STEM academic and career trajectories to become tangible outcomes, increased STEM career development could result. This might entail introducing students to STEM careers that they might not have previously experienced in their everyday life, community, or schooling, or even presenting the diverse STEM career possibilities that one wouldn't traditionally associate with STEM (Diekman et al., 2010; Wang & Degol, 2013). If we can begin to implement successful interventions that either maintain existing

STEM career intentions or further develops these aspirations, then we will become better equipped to minimize STEM education and workforce disparities.

STEM Major Selection

Findings regarding STEM major selection were not as expected given students' prior STEM career intentions. They do, however, align with STEM workforce and college statistics (Landivar, 2013). About 21 percent of students intended to select a STEM major, which is more than 10 percent less than the number of students who had previously said that they intended to pursue a STEM career in the prior wave of data collection. There were also many differences identified between who intended to select a STEM major in college. Looking within gendered groups, male students were more than two times as likely as female students to select a STEM major, and made up almost 65 percent of students who intended to select a STEM major. This was very different than the gender distribution of students intending to select a STEM occupation, where 42.6 percent of all females intended to pursue a STEM career compared to 25.7 percent of males.

Examining race/ethnicity, Asian students were the only group that had nearly identical percentages of individuals who intended to select a STEM occupation and those who intended to select a STEM major. All other racial/ethnic groups had a much less percentage of students intending to select a STEM major than what had been previously reported in terms of STEM career intentions. There was a about a 33 percent decrease from the number of White students who intended to pursue a STEM occupation to those who intended to select a STEM major, more than 50 percent decrease for Black students, and more than 60 percent decrease for Latino students. Looking at across race distributions of student STEM major intentions and comparing that to overall racial/ethnic distributions within the population, Whites and Asians were overrepresented, while Latinos and Blacks were underrepresented. Finally, with regard to socio-economic status, intentions of selecting a STEM major increased with each quintile, where nearly 70 percent of students intending to select a STEM major were from the highest two socio-economic quintiles.

There is something that must have happened between students' 11th grade year and when students traditionally begin college. Overall, and across race, gender, and socio-economic status, the percentage of students intending to select a STEM major greatly decreased from the amount that had reported intentions to pursue a STEM career during the previous year. The numbers were most troubling for females, Blacks, and Latinos. Groups underrepresented in STEM went from defying the norms (with regard to their high level of STEM career intentions) to mimicking the gendered and racial disparities present within STEM (with regard to their low level of STEM major selections). More than 42 percent of females intended to pursue a STEM career, 35 percent of Blacks, and 32 percent of Latinos. In contrast, 13 percent of females, nearly 14 percent of Blacks, and 17 percent of Latinos selected a STEM major. Further investigation is warranted to discover why Blacks, Latinos and females went from the groups with the highest within-group percentages of individuals intending to pursue STEM careers, to having the lowest within-group percentages of individuals intending to select STEM majors. More importantly, what influenced these discrepancies, and how can they be minimized in the future?

A potential factor contributing to the career and major intentions gap could be related to disparities in college entrance (Studley, 2003). Perhaps not all of those who intended to pursue a STEM career enrolled in college after high school. Many reasons could contribute to issues surrounding college enrollment (e.g., inaccessibility, affordability, academic preparation) (Long, 2014). Another reason could be that students simply chose other major and/or career trajectories. If this is the case, what happened between students' 11th grade year and their first year out of high school that may have changed their minds about their careers? Why is there such a substantial gap in numbers between STEM career pursuit intentions and STEM major selections? It is not enough for students to merely aspire to participate within the STEM workforce; relevant actions need to continually be engaged along the STEM trajectory. We need to at least get students to actually choose to major in STEM for there to be any chance of them becoming STEM professionals. Otherwise, we will remain limited in potential STEM prospects, and gendered, racial/ethnic, and socio-economic disparities within STEM will continue to prevail.

Overall, nearly 35 percent of students intended to pursue a STEM career. However, there was a substantial decrease in students' subsequent selection of STEM majors in college, where only 20 percent of students intended to select a STEM major. Decreases were greatest for females, Blacks, Latinos, and individuals within the lowest socio-economic quintiles. The demographics of individuals who selected STEM majors mirrored that of demographics present within STEM workforce trends (Landivar, 2013). It is pertinent that we engage efforts to increase STEM representation overall, but also target efforts toward marginalized groups to minimize the disparities in representation that exist in both STEM education and the STEM workforce.

Research Question 2

What is the relationship among cognitive, psychological, and environmental factors as related to high school students' intent to pursue a STEM career and selection of a STEM major?

For both the math- and science-specific models, all model elements were significant predictors, with the exception of a few of the environmental supports and barriers. Learning experiences were significant influences on self-efficacy and outcome expectation; self-efficacy and outcome expectation were significant predictors of interest; self-efficacy, outcome expectation, and interest were significant predictors of STEM career intentions; and self-efficacy, outcome expectation, and STEM career intentions were significant influences on STEM major selection.

Looking at environmental supports and barriers, neither math nor science teacher beliefs were predictors of STEM career intentions or STEM major selections, but science teacher expectations did have a negative influence on the relationship between students' science interest and their intention to pursue a STEM career. Only math teacher expectations were significant predictors of STEM major selections. Neither math nor science teacher expectations were significant predictors of STEM major intentions. They also did not moderate the relationship between interest and career intentions or career intentions and major selections. School informal STEM exposure turned out to be the most predictive environmental factor. It was a significant predictor of STEM major selection, and moderated the relationship between math interest and intent to pursue a STEM career.

Findings of this research suggest that teachers' beliefs might not be a significant factor influencing students' STEM career pursuits. In contrast, past research has identified teacher beliefs as significant influences on student beliefs and performance (Metheny, McWhirter, & O'Neil, 2008; Wang & Degol, 2013). Teacher beliefs, however, were found to be mediated by teacher-student interactions (Eccles, 2009). Thus, it could be the case that the insignificant influence of teacher beliefs on student career behaviors in this study is a representation of the impact of math and science teacher beliefs early on in students' high school journey (as students' 9th grade teachers' beliefs were used in the proposed model). It is possible that teachers' beliefs are more impactful later on in students' high school career, when interactions are more relevant, as students' career maturity is further developed. This perspective may need to be analyzed further in future research. However, as teacher beliefs may be significant influences on students' beliefs (as indicated in prior research) and student beliefs were found to be significant predictors of STEM career behaviors in this study, it is important for teachers to not display differential expectations, treatments, and stereotypes (Wang & Degol, 2013), especially with regard to populations underrepresented in STEM, if disparities in STEM participation are to be lessened.

In terms of STEM career development, results of these models suggest that students' learning experiences may be more influential than the conditions that exist within their school environment. Students' math and science identity was the strongest predictor among learning experiences. Additionally, self-efficacy was a stronger predictor of interest; outcome expectation was the strongest predictor of STEM career intentions; and STEM career intention was the strongest predictor of STEM major selection. Further, if we were to consider students' school environment, given the fact that there could be substantial differences between students' intention to pursue a STEM career and their actual selection of a STEM major, it seems that informal STEM exposure is the most important environmental factor influencing students' STEM career development. As such, it might be most beneficial to help students build positive and meaningful learning experiences through both formal instructional experiences and informal STEM exposure. Combined, these efforts could contribute to students' interest in, preparation for, and future participation within STEM careers.

Examining the student population overall, and the ways that we might facilitate STEM career development, these results suggest that we should help students cultivate positive math and science identities, which in turn impact their levels of self-efficacy and outcome expectation, and thus interest, STEM career intentions, and STEM major selection. A tool that can be used as a mechanism to build identity, self-efficacy, outcome expectation, and interest is the introduction of diverse forms of informal STEM exposure, which also directly and significantly influences students' selection of a STEM major. Perhaps we need to make STEM courses and subjects look more interesting to students. This could be achieved through interventions like offering short and powerful introductions that display multiple types of STEM professionals at work to entice students to think about STEM careers, matching students with STEM mentors, or any number of other forms of exposure to get students, especially those that are underrepresented, at least curious about the possibilities.

These types of interventions are suggested, as informal STEM exposure directly contributes to students' STEM informal learning experiences, which again is a significant predictor of both self-efficacy and outcome expectation. It is important to point out that while students' STEM informal learning was a significant predictor, it was not as strong of a predictor as math aptitude and math and science identity. I hypothesize that the limited types of experiences included in the measurement of informal learning participation in this study (i.e., participation in camps, competitions, programs, tutoring, and study groups) may have contributed to its strength. This is especially true when considering the abundance of other STEM exposure activities available, as demonstrated by the types of activities included within the measurement of schools' informal STEM exposure (e.g., field trips, mentorship, guest speakers, college partnerships, promotion of STEM opportunities available in the community).

Research question two examined the relationship among cognitive, psychological, and environmental variables, and how this relationship influenced students' STEM career development. Overall, results indicate that students' learning experiences, diverse sources of informal STEM exposure (which contributes to the types of informal STEM experiences students encounter), students' self-efficacy beliefs, and students' outcome expectations are significant influences on their development of STEM interest. STEM interest then results in the formation of STEM-oriented career goals, which directly influence STEM-related academic pursuits. Each of these is a building block that helps move students toward future STEM workforce participation.

Research Question 3

Are there differences in how math-related core Social Cognitive Career Theory predictors (i.e., math- self-efficacy, outcome expectation, and interest) influence STEM career intentions and major selection, based on gender, race/ethnicity, or socio-economic status?

Three models were examined for potential group difference—a gender-based model, race/ethnicity-based model, and a socio-economic-based model. In some instances, there were only subtle differences between groups, and in others, the differences were substantial. Discussion of each model is presented below.

Gender Model

Comparison of the core math model by gender yielded very few differences. In fact, all regression paths were significant for both groups, with the exception of the influence of outcome expectation on STEM major selection for female students. Additionally, three regression coefficients were constrained equal, as there was no difference of association between relevant factors for males and females. These were the influence of self-efficacy on intent to pursue a STEM career; outcome expectation on intent to pursue a STEM career; and self-efficacy on STEM major selection. For all other regressions that were significant for both males and females, the strength of association between factors was fairly similar.

The margin between male and female students' math outcome expectation mean score was minimal. On average, males did have a higher level of outcome expectation, but this was also true for many of the other constructs in the model. So, why was this particular difference so significant—and so much so that outcome expectation was not a significant predictor of STEM major selection for female students? When initially identifying the lack of significance of outcome expectation as a predictor of STEM major selection, I thought that female students' math outcome expectation was so low (i.e., nearly zero), that it did not have the power to be predictive in the model. That theory quickly diminished, as outcome expectation significantly predicted both interest and

STEM career intentions for females, which is consistent with tenets of Social Cognitive Career Theory (Lent et al., 2002).

Could it be the case that despite outcomes female students might expect of math, those beliefs just do not play a major role in their decisions regarding STEM major selection? Prior research has suggested that occupational values differ between male and female students (Wang & Degol, 2013). While males tend toward work with machines, objects, and tools, females tend toward people-oriented careers (Wang & Degol, 2013). As such, gender preferences and occupational values play significant roles in female students' underrepresentation in STEM (Wang & Degol, 2013). Overall, however, the Core Math Model was predictive of students' STEM career behaviors for both male and female students, with marginal group differences observed.

Results from this study combined with findings in the literature indicate that we might want to present opportunities in STEM from a more people-oriented perspective to attract more female students. This could also point to why female students in this study were more inclined to want to pursue health occupations than occupations in life and physical sciences, engineering, mathematics, and information technology. When STEM is presented as more communal, female students' interest increase, thus fields like biomedical and civil engineering attract more female students than fields that work less with people, like mechanical or nuclear engineering (Gibbons, 2009; Wang & Degol, 2013). Framing STEM in a communal, people-oriented lens could be what is necessary to facilitate female students' inclination to commit to STEM workforce participation, thus decreasing gender-related disparities.

<u>Race/ethnicity Model</u>

Examination of the core math model by race/ethnicity yielded a few similarities. Three regression coefficients were constrained equal, as there was no difference of association between relevant factors across race/ethnicity. These regressions were the influence of self-efficacy on interest; the influence of outcome expectation on interest; and the influence of STEM career intention on STEM major selection. Additionally, while the regression coefficients were not equivalent across groups, self-efficacy was a significant predictor of outcome expectation for all races/ethnicities.

However, there were also major differences observed between racial/ethnic groups with regard to the predictability of the Math Core Model. The model most successfully predicted the STEM career development process of White students, where all model regressions were significant, with the exception of the influence of self-efficacy on STEM career intentions. The model was moderately predictive of Asian students' STEM career development. With the exceptions of the influence of self-efficacy on STEM career intentions and outcome expectation on STEM major selection, all hypothesized paths were significant. In contrast, the model was least predictive of Black students' STEM career development. None of the hypothesized predictors of STEM career intentions were significant. In addition, neither self-efficacy nor outcome expectation were significant predictors of STEM major selection. The model was not as successful in predicting Latino students' STEM career development, either. For Latino students, only self-efficacy turned out to be a predictor of STEM career intention and STEM major selection. Interest and outcome expectation were both insignificant.

These results are a lot different than those discussed when speaking about the entire math model that was analyzed with respect to the whole student population, and that of the gender-based core math model. Findings of the race/ethnicity multi-group model demonstrate that while particular frameworks may prove to be effective for certain populations, they may not be applicable to others. This is especially important to consider when potential group differences are concealed. In the comprehensive math model that was analyzed using the entire high school population, all racial/ethnic groups were combined; thus, we were unable to fully discern potential group differences that might actually have been present. We assumed equality among groups. We also supposed that model effects were equivalent across groups. Multi-race analyses, however, provided insight that these assumptions were flawed. It also shed light onto the notion that while theoretical frameworks might in fact be predictive, as supported by prior research, they may not be universally applicable. Moreover, if we continue to use the same types of samples in our research, and/or make the same sorts of assumptions regarding group equivalence, we may never identity these anomalies. Consequently, they may never properly be addressed.

Socio-economic Model

Examination of the core math model by socio-economic status yielded similarities. Two regression coefficients were constrained equal, as there was no difference of association between relevant factors across socio-economic status. These regressions were the influence of self-efficacy on interest and the influence of STEM career intention on STEM major selection. Additionally, while the regression coefficients were not equivalent across groups, two other regressions were significant for all groups. These were the influence of self-efficacy on outcome expectation and the influence of outcome expectation on interest. Lastly, for all groups except students in the second quintile, self-efficacy was a significant predictor of STEM major selection.

There were also many differences observed. The model was most predictive for students in the highest socio-economic quintile. For students in this group, all hypothesized paths were significant, except the influence of self-efficacy on STEM career intentions. The model was moderately predictive for students in the fourth socio-economic quintile. With the exceptions of the influence of self-efficacy on STEM career intentions, and outcome expectation on STEM career intentions, all model hypotheses were significant. In contrast, the model was least predictive for students in the third socio-economic quintile, where none of the hypothesized predictors of STEM career intentions were significant, and outcome expectations was shown not to be a predictor of STEM major selection. Similarly, for students in the lowest and second quintile, the model failed to be a significant predictor of STEM career development, as three of the hypothesized paths were insignificant for both groups.

Across all multi-group models, it seems that STEM career intention was most difficult to predict. Furthermore, self-efficacy was least predictive of STEM career intention and outcome expectation was least predictive of STEM major selection. Overall, differences in model prediction based on group membership were apparent. The model was not a consistent indicator of STEM career development for all students. This calls for more varied analyses within the research community, where the possibility that there are differences between individuals (due identity complexities) is both acknowledged and addressed in the methodology.

Challenges, Limitations, and Strengths

There were several challenges encountered while conducting this research due to factors relating to the nature of data used, research design, and statistical software. Additionally, those factors contributed to limitations and strengths of this study. The most significant challenges, limitations, and strengths are discussed below.

Challenges

Large-scale Data

Many of the challenges experienced were due to the use of complex data. There are a host of intricacies intrinsic to large-scale data. Trials encountered were related to understanding HSLS:09's sampling procedures, missing data, imputation methods, design/sampling weights, sampling units, data levels, data navigation, naming conventions, composite variables, public versus restricted information, data types, and so forth. The data itself was also intimidating; there were so many components that it quickly became overwhelming. I had to read HSLS:09's documentations and codebooks. I participated in webinars on large-scale data. I attended sessions on utilizing NCES data. I watched all of HSLS:09's instructional videos. Essentially, before I was able to delve into the data for research engagement, I was required to do a lot of background preparation, just to equip myself with a baseline understanding.

Due to the use of a two-stage sampling design, where in the first stage schools were selected using stratified random sampling, then during the second stage, students were randomly sampled, High School Longitudinal Study of 2009 had to employ complex procedures to assure that the appropriate design effect weights were applied to the data (Ingles et al., 2011). To protect against clustering effects (i.e., biases resulting from shared experiences of students attending the same schools and/or classes), design effect weights for each wave of data (i.e., base year, first follow-up, and update) were developed. Additionally, for the data to maintain its generalizability to high school students across the nation, efforts needed to be taken to assure that the study population was representative of the larger public. Certain subgroups were deliberately oversampled so that between group analyses could be conducted and maintained the appropriate statistical power. Thus, to counter these biased effects and preserve generalizability, sampling weights were developed.

One of the challenges encountered surrounded the use of different levels and years of data. My analytical model contained data from the first, second, and third waves of data, as well as student, teacher, and school level data. In turn, I had to use the appropriate analytical weights, which were a combination of design effect weights and sampling weights. Particular analytical weights were provided by HSLS:09, which were combinations of the most likely types of analyses they felt would be conducted.

Multiple Levels of Data

One of the first analytical obstacles faced surrounded the inclusion of school and student level data in the same model. Originally, I had planned to use both students as a unit of analysis and schools as a unit of analysis, each for their associated levels of data. However, this would have meant using two separate data sets, which would have further complicated analyses, as it would have required multi-level modeling. Fortunately, for ease of analysis, HSLS:09 transformed school-level data to the student-level as a form of contextual information. Similarly, math and science teacher data were also included in the student dataset, as forms of contextual data, to better illustrate students’ environmental conditions. In turn, only one level of data was required in the analysis, thus simplifying statistical efforts.

Selecting Appropriate Analytical Weights

Next, issues were faced surrounding selection of the appropriate sampling weights. Again, analytical weights were based on particular waves of data (i.e., base year, first follow-up, update) or longitudinal analysis (i.e., a combination of waves of data), as well as stakeholder (i.e., students, parents, math teacher, science teacher, or school administrators/counselors). Due to my model's inclusion of multiple stakeholders and waves of data, I had to determine which sampling weight was most appropriate in terms of best representing the population given variables included within the model. This proved to be challenging, as the set of survey weight combinations created by HSLS:09 was not exhaustive. Thus, in certain instances, there were no survey weights that perfectly fit the complexity of my model. An example is the multi-group analysis by socio-economic status. The most ideal analytical weight would have been one that combined the last two waves of data, as well as student- and parent-level data. However, no such weight existed. Consequently, I had to make tradeoffs based on what was available to me, and chose a weight that I felt would make the most sense analytically (i.e., wave 2, with student and parent level data).

Statistical Learning Curve

A challenge inherent to research involving new statistical methods and/or software is the learning curve. Prior to this research, I had very limited experience with structural equation modeling, Mplus, or WarpPLS, thus had to build proficiency in all. I took a structural equation modeling course to strengthen my understanding of its core underpinnings and related techniques. Next, I had to learn how to use both Mplus and WarpPLS software. With regard to Mplus, one of the toughest learning curves was the software's use of syntax. Additionally, the interface wasn't very user-friendly. Conversely, WarpPLS was largely point and click, and walks users through each step of the modeling process. To support my understanding and combat some of the many challenges faced during my use of each of these software, I read each software's user guide, watched video tutorials, sought the guidance of my methodologist, visited relevant forums, and contacted each software's developers with inquiries. This took place throughout the research process.

Modeling Moderation

During the actual analysis, a challenge encountered was modeling moderating effects in the Mplus software. Before I was even able to test the moderating effects, I had to first create the interaction terms within the software, as these variables were not included in the original data (six all together). After creating the interaction terms, I was able to run the model. However, for some reason, Mplus took issue with the model's moderation, and reported an ill-fitted model. Originally, my methodologist and I thought that the problem was with the interaction terms themselves; perhaps there was an issue during the creation of these variables within Mplus. Thus, my methodologist recommended trying to create the interactions in SPSS first, import the new dataset into Mplus, and then try modeling moderation again. After taking those steps, Mplus still reported an ill-fitted model. We could not figure out why this issue persisted. We then decided that it might be best to use WarpPLS software for models that included moderating effects. Within WarpPLS, moderations were created without issue, and the models were well-fitted. However, while WarpPLS was able to model moderating effects, the use of analytical weights was not allowed.

Testing Multiple Analytical Model Structures

Finally, one of the most tedious and time consuming challenges faced was testing multiple analytical model structures. In the initial phase of the research, I continued to build onto the models as I was learning how to use the software, as each additional component was an added level of complexity. To assure that I understood what each command was doing, and where potential issues arose, I created and tested different pieces of the model, then combined them all to create the final model. This was conducted in both Mplus and WarpPLS. Next, for each model structure, I had to create a math-specific model and science-specific model, since constructs were separated by math and science. Then, during multi-group analyses, each group-specific model (e.g., gender) was run to get a baseline model. Based on the baseline model, regression paths that could potentially be equivalent across groups were identified. Next, several models were tested where relevant paths were constrained equal as a means of locating group difference. Finally, a final model was created and tested, where certain regressions were constrained equal and others were freely estimated based on the results of prior model testing. This process was conducted for multi-groups analyses of potential gender, racial/ethnic, and socio-economic difference. Overall, during the entire research process, an estimated 50 models were created and tested.

In light of the challenges encountered, due to the nature and depth of conversations held with the statistical software developers and my methodologist, there is great confidence that all analyses were conducted appropriately, with logic, and in alignment with research purposes. Further, statistical processes engaged were as accurate as statistically possible, given standard expectations for error associated with all quantitative analyses. As such, I am satisfied with this study's results, and can assure with confidence that findings are both accurate and meaningful.

Limitations of the Study

Use of Extant Data

One of the limitations of the study resulted from the use of extant data. I used pre-existing data, therefore, was unable to choose which constructs were included in the original study, or how the constructs were measured. This was particularly limiting with regard to teacher beliefs, STEM occupations, student informal STEM experiences, and student beliefs. In terms of teacher beliefs as used in my model, in the original study, this construct was named teacher self-efficacy. However, the indicators that were used to measure this construct seemed to be more in line with teacher beliefs about their students, rather than their levels of self-efficacy regarding their teaching practices. As such, I felt it more appropriate to name this construct in a manner that best represented how it was operationalized. Though the construct still provides meaningful insight into teacher attitudes and beliefs, and thus contextual information regarding students' school environment, it did not measure what I had originally anticipated when seeing the variable in the data.

While the title that I had given this construct may be appropriate in some fields (e.g., instructional design, within the attitude literature), a limitation of my naming this variable "teacher beliefs" is that "teacher beliefs" as a construct is operationalized differently within teacher education. I am mindful that there may be differences in the use of and meaning behind constructs across disciplines, and recognize that this may inherently results in conflicting uses and interpretations of terminology. Unfortunately, no other word or phrase seemed to capture this construct as measured by the indicators in the data more appropriately. The term “teacher beliefs” made the most sense conceptually thus was used within the context of this study.

The teacher expectations construct within the data actually measures teachers’ perceptions of other teachers’ expectations. I would have preferred for teachers to report their own expectations of their students, rather than their perceptions of how their colleagues felt. Again, still telling in terms of perceived teacher and/or school culture, and thus serves as a form of contextualization of students’ school experiences, but not what I would have selected or what I had anticipated when originally seeing this variable.

With regard to student STEM informal learning experiences, summer programs, competitions, clubs, tutoring, and study groups were all included as informal activities within the study. However, after conducting analyzes and seeing that study groups and tutoring were most engaged by students, I think a different perspective could have been offered if informal learning was broken down into two types (i.e., developmental for tutoring and study groups, and enhanced exposure for summer programs, competitions, and clubs). There may be differences in why people choose to engage in the two categories of informal learning, which could be related to different STEM outcomes. I anticipate that students who participate in summer programs, clubs, and competitions might have an increased likelihood of engaging in STEM academic and career pursuits.

Additionally, students' math and science self-efficacy, outcome expectation, and interest were each measured with regard to their current math or science course as opposed to math and science more generally. While the reliability of student responses might have been stronger due to specifying particular courses, it was still a very narrow and focused measure of beliefs. Perhaps student responses didn't represent their overall beliefs about math or science, respectively, thus potentially limiting how one might interpret relationships to other model constructs, and most importantly, it's prediction of STEM career pursuits and major selections. While I see the value of measuring self-efficacy, outcome expectation, and interest within the context of current course enrollment, I would have measured these constructs more generally. Furthermore, limiting context to current course enrollment also restricted who was able to answer on the questionnaire; only students currently enrolled in math or science courses were allowed to respond to the associated items measuring their beliefs. This impacted missing data.

Finally, occupations were only available in broad categories. Data were not available to examine specific STEM domains. I would have liked to tease out relationships between model constructs and particular STEM occupations and/or majors, but due to the nature of the data structure, that was not possible.

Although some data points were not exactly what I had hoped for, High School Longitudinal Study of 2009 is the most comprehensive longitudinal dataset available, and provides all measures that align with the research questions asked in this study. Further, data quality is excellent, allowing for high reliability of application. As in any data analysis, there will be limitations. However, overall, the results derived from use of these data are representative of the concepts and phenomena being studied.

Intersectional Analysis and Structural Equation Modeling

A limitation of this study was that intersectionality was not engaged within the context of structural equation modeling. Intersectional analyses require large sample sizes to make meaningful interpretations of the overlap among identity categories. Similarly, for strong statistical power within structural equation modeling, large sample sizes are required. While the sample in the study was very large, it may not have been enough to run a SEM model on each subgroup resulting from intersectional approaches. Additionally, due to the complexity of the model, the number of models I had to develop and test, all other analyses conducted for this study, and time constraints, intersectional SEM was simply infeasible. Although SEM techniques engaged were not as comprehensive as would have been ideal, statistical approaches conducted were acceptable, and produced meaning results.

Strengths of the Study

Large-scale Data

Major strength of this study stemmed from the use of HSLS:09. Due to the substantial sample size, I was afforded that ability to conduct statistical analyses with great statistical power. Additionally, the quality of data was high, also allowing for quality results. This study included student level data, as well as school-related contextual data, thus allowed for a comprehensive examination of students' academic experiences as related to their STEM career development.

Intersectional Approach

Another strength of this research was the inclusion of an intersectional approach during descriptive analyses. I was able to gain extensive insights into individual differences when considering the complexity of our multiple identities. When conducted, analyses of group difference typically compare across race, gender, or socio-economic status. However, we have more than one identity, thus our experiences may range greatly. For example, Asian males and Asian females may have different experiences. These experiences may become even more varied when introducing socio-economic status. This research was able to capture some of those complex nuances, and thus, became one of this study's major assets.

Multi-group Structural Equation Modeling

The final major strength of this study was the comparison of the proposed model by gender, race/ethnicity, and socio-economic status. Most research involving models employing a Social Cognitive Career Theory framework utilizes predominately White samples. Additionally, analyses are typically conducted with only one group. Thus, results aren't necessarily generalizable to other populations. Not only was this study's population nationally representative, each subpopulation was large enough to allow for multi-group comparisons using structural equation modeling. I was able to identify which subpopulations the model successfully predicted, and the subpopulations for which the model was less fitting. Not only did these analyses highlight potential group differences, it also shed light onto the notion that not all frameworks are appropriate for all populations.

<u>Implications</u>

Implications for Instructional Design

Within instruction design, it has always been asserted that instruction needs to be designed and developed with audience and environmental conditions taken into consideration. Going further, however, this study has demonstrated that instructional designers creating instructional interventions to help facilitate STEM participation should also be attentive to within group differences. This research has highlighted that while self-efficacy, outcome expectation, and interest can be significant predictors of STEM career development, influence of each might look differently when considering students' gender, race/ethnicity, and socio-economic status. For instance, if the audience is primarily Black and the goal is to aid in cultivating positive STEM career intentions, instruction that centers around developing heightened levels of STEM self-efficacy, outcome expectation, and interest may not be effective, as this research has demonstrated that those constructs were not significant predictors of intent to pursue STEM careers among Black students. Furthermore, intersectional analyses suggest that even within a particular group, differences can still exist based on other identity categories at play. There were substantial differences between Black female students in the lowest socio-economic quintile, and those in the highest in terms of math aptitude, STEM career intention, and STEM major selection. Thus, in the most optimal of circumstances, instruction should also be differentiated to meet the unique needs of the population's diverse subgroups. Finally, there is no real way of knowing where differences might exist, thus instructional differentiation should be based on various sources of empirical evidence.

Instructional designers using this research to inform practice should interpret findings of this research carefully; false assumptions or flawed implication can easily be made. These findings do not suggest that constructs core to SCCT are not pertinent to Black, Latino, or low socio-economic students' STEM career development, or that efforts aimed at aiding students in cultivating increased self-efficacy, heightened interest, or positive outcome expectations should be neglected. Building these self-concepts and dispositions has not been shown to negatively impact students in this research. This study does, however, suggest that the nature of the relationship between these constructs as postulated by SCCT is not predictive of STEM career development for these students. Perhaps these constructs are related to STEM career development in different ways. There may even be additional factors that need to be included in the model to better explain how these groups of students undergo STEM career development. Or, it could very well be the case that these factors are not significant to STEM career development for Black, Latino, and low socio-economic groups, but rather an entirely different set of factors may show to be pertinent to their STEM career development. Essentially, one of the most important key points that instructional designers should take away from this research is that the SCCT model does not work for Black, Latino, and individuals from socio-economic backgrounds.

Overall, this research is significant to the field of instructional design. It demonstrates that even empirically valid frameworks have limitations. Social Cognitive Career Theory is one of the most widely used frameworks, which has been applied to various disciplines, with regard to diverse contexts, and across different types of populations, but does not predict STEM career development for racial/ethnic minorities nor individuals from low socio-economic backgrounds. Instructional designers working with these groups should not base interventions on this perspective. Instead, instructional designers need to identify alternate frameworks that are predictive of STEM career development, but also scrutinize these tools to assure applicability to these groups. While findings of this research cannot inform instructional designers of what types of interventions should be implemented or even how they should be designed, it does inform instructional designers that developed interventions should not be based on this framework for particular groups (but is indeed predicative for others). Otherwise, efforts aimed at facilitating STEM career development may prove to be ineffective.

Implications for the STEM Workforce

Analysis of students' STEM career intention suggested that there was substantial interest in pursuing STEM occupations. The awareness of and intention to pursue STEM was there. This was true for all students across gender, race/ethnicity, and socio-economic status. In most cases, the numbers were most significant for those that are traditionally under-represented within STEM. The issue, however, was in maintaining that interest. Something happened in the period between students' consideration of pursuing STEM careers, and their selection of a major during their eventual entrance into college. There was a drastic decrease in numbers from those who reported intentions of pursuing a STEM career during their 11th grade year of high school, and those who actually selected/planned to select a STEM major at the start of college.

This suggests that we need to engage increased retention efforts, even prior to formal STEM entrance at the start of college. There was so much possibility for the workforce, but that potential quickly dwindled in such a short period of time. These efforts need to be especially targeted toward females, Blacks, and Latinos if we want to minimize disparities in STEM participation. There was between a 50 and 70 percent decrease from STEM career intention to STEM major selection among students in these groups. Retention efforts must also be appropriate for the group being targeted, as demonstrated in the multi-group analyses of STEM career development models. Otherwise, efforts may be ineffective, and inequities with regard to representation within STEM will continue to persist.

Finally, the operationalization of the STEM workforce needs to be more consistently defined. Differences in the types of careers included within STEM by various stakeholders add to confusions regarding the true composition of individuals making up this workforce. This then impact understandings regarding who persists and who drops out of the STEM pipeline. Some stakeholders question the validity of their exclusion from the workforce, like K-12 STEM educators, as they encompass STEM-related knowledge, apply it daily to their teaching practice, and groom students to develop the capacity to become future STEM professionals. However, while STEM instructors in post-secondary sectors are included as STEM professionals, K-12 educators are not, and instead are classified under branches of teacher education or professional development.

While I do not know how the STEM workforce should be defined, I do think that there is a need for diverse groups of stakeholders to come together and establish a system, or at least better define what it means to be a STEM professional. Once a more collective understanding of the STEM workforce is reached, alignment between sectors of the STEM workforce and disciplines of STEM majors need to be conducted. Once we finally achieve consistency in the definition of STEM, and alignment between stages of the

STEM pipeline, progress toward building STEM capacity within this nation could less likely be impeded.

Future Research

The field could benefit from additional research on the application of Social Cognitive Career Theory, and career development frameworks more generally, both to STEM and across diverse populations. Generalizability of these frameworks is often based on White, middle class populations. However, the larger public is a lot more diverse. Even more informative would be the inclusion of multi-group analyses within the context of the same study. This would provide insight into potential group differences, given equivalence in measurement. These techniques could help to identity which predictors are significant influences on STEM career development, and for which populations. STEM career development processes might not look the same across groups, as demonstrated in this research, thus expanding our efforts to be more inclusive and exhaustive could prove to be insightful.

Additionally, future research should engage intersectional approaches to quantitative analyses. We are more than individual identity categories, or even the sum of multiple identities. Our identities need to be examined simultaneously, thus representing a more multiplicative approach to understanding identity complexity. Our experiences can differ greatly depending on the entirety of our demographic makeup. Developed interventions and/or derived recommendations resulting from research endeavors could potentially be more effective in facilitating change if they are targeted appropriately. It is important to note that intersectional analysis is not and should not be limited to gender, race, or socio-economic demographics; it can be applied to any phenomena where subjects could belong to and/or be described by multiple categories.

Moreover, in addition to large-scale quantitative studies, the field would benefit from nationwide coordinated qualitative studies that investigate some of the *why* and *how* questions generated from this study's findings. For example, what happened between students' high school and college timelines that may have led to changes between students' STEM career intentions and their subsequent selection of STEM college majors? Or why were there differences in students' informal STEM learning experiences (e.g., participation in math and science clubs, competitions, programs) based on gender, racial/ethnic, and socio-economic status? Essentially, a series of smaller and targeted qualitative studies may be insightful.

Finally, it was unfortunate that equity was outside of the scope of this research, as this study focused primarily on understanding STEM career development. However, there is a dire need for future research on STEM career development to situate STEM participation within the context of equity, especially with regard to marginalized populations. The two are rarely discussed in conjunction, but the relationship is important. STEM workforce participation can substantially influence equity, both with regard to persons and their community. It is important that this perspective is included in discussions of STEM workforce participation and STEM workforce growth. It speaks to implications that extend beyond the national economy and workforce strength. Instead, it highlights the effects of STEM participation experienced by individuals and their communities, and the subsequent changes surrounding equitable outcomes that could potentially result.

<u>Final Conclusions</u>

This research uncovered the various nuances of STEM career development. The most significant take-away from this research is that the STEM career development process, and all of its defining constructs, look differently depending on students' personal characteristics. While the analytical models that were explored in this study were largely successful at predicting the STEM career development process of the high school population overall, predictability varied greatly when considering particular sub-group characterizations.

Thus, while I might not fully understand the nature of STEM career development for all demographic groups, this research has proven to be insightful in many other ways. Most rewarding was recognizing that a large portion of students, from *all* subgroups, had developed this interest in and intent to pursue STEM occupations. It is true that those intentions seemingly decreased by the time students enrolled in college, but the potential was there nonetheless. We now need to ascertain the means to leverage that potential, so that STEM academic and career participation can be transformed from distant possibilities to actual realizations.

Appendix A: Email from Office of Research and Integrity Protections regarding IRB Review

Question Regarding Exemption -- IRB Review Not Required

EO

Email AAF orip <orip@syr.edu>

Fri 1/20, 3:32 PM

Tashera Nigia Bolds

Reply all

Inbox

This message was sent with high importance.

Action Items

Hi Tashera,

Thank you for your telephone call and e-mail in regards to your research study. Please note that I was able to hear back from IRB Office Director Tracy Cromp and because you are using publicly available, de-identified data your research does not meet the definition of human subjects research and does not require IRB review and oversight. Therefore, you does not have to complete the IRB application.

Thanks again,
Christopher
Syracuse University
Office of Research Integrity & Protections
214 Lyman Hall
orip@syr.edu

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Syracuse University, Syracuse, NY
M.S. in Instructional Design, Development and Evaluation **2013**

Syracuse University, Syracuse, NY
B.A. in Mathematics and Sociology, *Cum Laud*e **2011**
Sociology Honors Thesis: "Doing the Mathematics on Urban Youth: Understanding How African American Students Living in Urban Society Make Sense of Mathematics"

SCHOLARSHIPS, HONORS, & AWARDS

STEM Fellowship, Syracuse University	**2013-2017**
Master's Degree Prize, School of Education, Syracuse NY	**2013**
Burton Blatt Scholarship, Syracuse University	**2012-2013**
Burton Blatt Scholarship, Syracuse University	**2011-2012**
Graduate Scholarship, Syracuse University	**2011-2012**
Distinction in Sociology, Syracuse University	**2011**
Alpha Kappa Delta International Sociology Honor Society inductee	**2011**
McNair Scholar, Syracuse University Chapter	**2009-2011**
SMART Scholarship, Syracuse University	**2009-2011**
Founder's Scholarship, Syracuse University	**2007-2011**
S.U. Merit Scholarship, Syracuse University	**2007-2011**
Gates Millennium Scholarship, Gates Millennium Scholars Program	**2007-2016**

PROFESSIONAL EXPERIENCE

Hezel Associates, LLC, Syracuse, NY
Consulting Research Analyst **2016-2017**

Hezel Associates, LLC, Syracuse, NY
Research Assistant **Summers 2015 and 2016**

Instructional Design, Development & Evaluation, Syracuse, University, Syracuse, NY
Graduate Research Assistant **2014–present**

ERAU Aviation Institute, Daytona Beach, FL
Instructional Designer **2012–2013**

Math and Movement, Ithaca, NY
Research and Instructional Design Intern **2012**

Department of Sociology, Syracuse University, Syracuse, NY
Undergraduate Research Assistant **2011**

Huntington Learning Center, Fayetteville, NY
Math and Science Instructor **2008-2009**

Department of Philosophy, Syracuse University, Syracuse, NY
Undergraduate Teaching Assistant **2008-2009**