ABSTRACT

ALEXANDER, ALONZO BRANDON. Exploring Student Attitudes and Outcomes toward STEM Careers after Repeated Participation in STEM Outreach. (Under the direction of Dr. Eric Wiebe).

A wide range of efforts has been explored to fill the United States' need for professionals in the field of science, technology, engineering, and mathematics (STEM). Understanding the factors that influence student persistence in out-of-school educational spaces such as outreach programs is important to meeting this demand. Outreach programs are interventions designed to both educate and motivate students about potential STEM careers and have been shown to serve as a key strategy for increasing the student attitudinal measures of self-efficacy and outcome expectancy (in this study referred to as future academic performance), which both relate to persistence (Vennix et al., 2018). Understanding the potential differences of how person-level factors (e.g., ethnicity and gender) and program-level factors (e.g., types of schools served and geographical location) relate to persistence is critical to keeping STEM Pathways open to students of all backgrounds, but particularly to underrepresented minorities (URMs). Using the S-STEM survey instrument developed by the Friday Institute at North Carolina State University, this study examined factors directly related to the outreach participants such as race, gender, repeated attendance, and self-reported measures of self-efficacy and future academic performance in relation to their measures of STEM self-efficacy and their stated intent to choose a STEM major in college. This analysis looked across multiple programs offered at North Carolina State University (NCSU) and partnering outreach locations. Because of the nature of the data, i.e., students as repeated participants nested into programs, a multilevel analysis that could account for repeat measures was required.

A mixed effects multilevel analysis determined that there were significant relationships between personal level and program level factors for STEM self-efficacy and student intent to major in a STEM field. Approximately 7600 students from grades K-13 participated in the S-STEM survey and were included in the analysis. The first question sought to determine the relationship between person-level factors and STEM self-efficacy. The results determined that there was a significant relationship between numerous person-level factors and STEM self-efficacy. Factors such as gender, race, and repeated participation in STEM outreach were significant in predicting levels of STEM self-efficacy.

A second question investigated the relationship between personal and program level factors and students' intent to major in a STEM field. Contrary to prior research, the results indicated that there is a significant relationship between race, gender, and student intent to major in STEM. Additionally, reported measures of mathematics and science self-efficacy were significantly correlated with higher intent to pursue STEM. Finally, an analysis of the outreach programs revealed that while their potential impact on both STEM self-efficacy and student intent to major in STEM were small, certain types of programs, namely those in the biologically-oriented STEM areas, seemed to more consistently have a positive impact on these measures.

Exploring Student Attitudes and Outcomes toward STEM Careers after Repeated Participation in STEM Outreach

by
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APPROVED BY:

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Dr. Soonhye Park	Dr. Jason Painter

DEDICATION

This work is dedicated to my grandparents Bessie and Alexander Tuck, for showing me how to love, to my wife Janelle for allowing me to love her, and to my children Fran and Zoz for giving me people to love more than myself.

BIOGRAPHY

Alonzo Brandon Alexander is a North Carolina native. Born in Durham, raised in the small town of Norlina, NC, he earned his B.S. degree in Physics and his M.Ed. in Physics Education from Florida A&M University (FAMU) in 2007 and 2012, respectively. As a researcher specializing in plasma physics, Alonzo spent time working on cutting edge fusion technology while at Lawrence Livermore National Laboratory in Livermore, CA, before returning to his alma mater to serve as the lead technician on the Spheromak Turbulent Physics Experiment (STPX), which became the first fusion experiment to achieve first plasma at any historically Black college or university. While working at FAMU, he taught several physics courses, igniting his passion for education. Alonzo went on to teach middle grade science and high school physics and chemistry at both public and private Florida schools. A scientist to his core, his goal was to help young students think of themselves as scientists too. Alonzo's interest in STEM outreach led him to work with many different programs throughout his time in Florida, an interest he continued to serve when he returned to NC. As a graduate research assistant at The Science House at NC State University, Alonzo has worked primarily with underserved students in the Imhotep and Kyran Anderson Academies Programs to develop their interest and passion for STEM careers. Alonzo married the love of his life in 2007 and she continues to tolerate him as they raise their two wonderful and talented children.

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Chapter One: INTRODUCTION

The push to increase the number of Americans engaging in science, technology, engineering, and mathematics careers is not a novel approach in the United States. As early as the 1950s, scientists, engineers, and mathematicians were recruited by the American government to make sure that US innovation kept pace with Soviet achievements. The launch of Sputnik in 1957 became an inflection point for collective scientific and technological growth at previously unseen levels, all to the benefit of the U.S. educational system. However, despite post Space Race advances, by the 1980s many in education became concerned about student academic performance, with particular concern that students' lack of science and math achievement was leading to the loss of the scientific and technological advantage of the U.S. over the rest of the world. The landmark report, A Nation at Risk: The Imperative for Educational Reform, stated those concerns in no uncertain terms: "Our once unchallenged preeminence in commerce, industry, science, and technological innovation is being overtaken by competitors throughout the world…" (National Commission on Excellence in Education, 1983, p. 9). Arguably the most important recommendation from that report was to both emphasize and standardize science and math education, including an emphasis on their connection to both technology and engineering. It was believed that an earlier educational focus on what are now called 'STEM' (science, technology, engineering, and mathematics) fields would better prepare students for future careers in interdisciplinary STEM jobs.

By the late 1980s "STEM education" as a term became genericized by the National Science Foundation for any educational program, practice, or event related to a STEM discipline (Bybee, 2010). A report from the United States Bureau of Labor Statistics noted that more than 9 million people work in STEM-related professions (Fayer et al., 2017). However, this is less than

6% of the total US workforce. Additionally, more than half of these STEM jobs are only in computer and math related fields. Figure 1.1 reveals that the U.S. is third globally in the total number of STEM majors produced and American colleges and universities. However, the ratio of STEM to non-STEM decrees in the United States is relatively low when measured against similarly prosperous nations, ranking 27th out of 29 for percentage of STEM degrees awarded relative to the U.S. population (Thompson & Bolin, 2011).

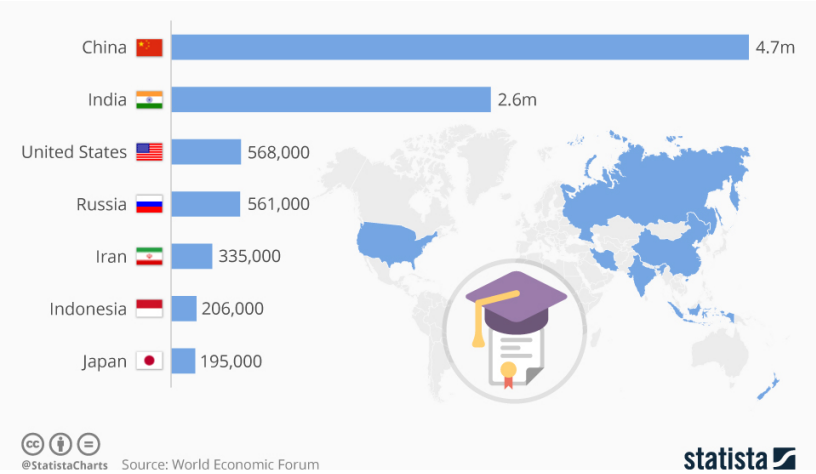

Figure 1.1. Global Comparison of Total STEM Graduates in 2016
Recent graduates in Science, Technology, Engineering and Mathematics by Niall McCarthy is licensed under CC BY 2.0.

When compared other industrialized nations, as seen in Figure 1.2, the U.S. rate of STEM graduates to total graduates is less than half that of nations ranging from large countries like Germany to smaller nations like Singapore.

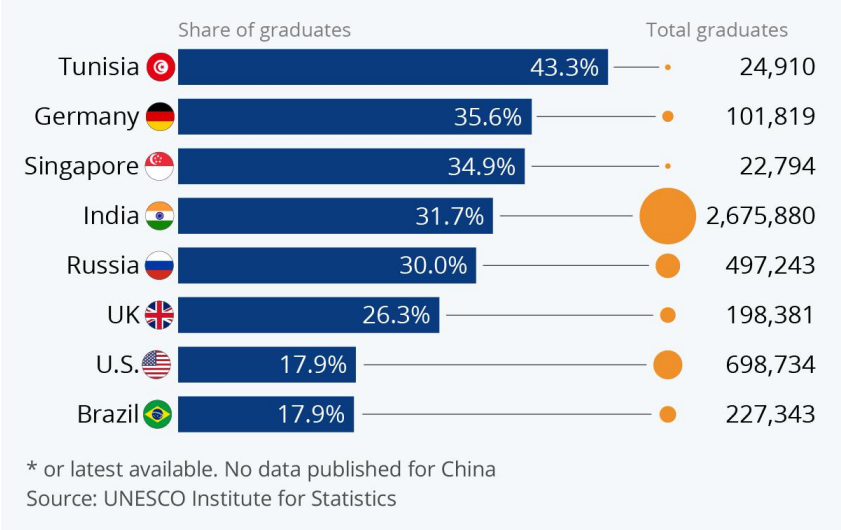

Figure 1.2 Share of STEM Graduates to Total Graduates as of 2018 Where Most Students Choose STEM Degrees by Katharina Buchholz is licensed under CC BY 2.0.

In the last 10 years, STEM occupations have grown nearly 20%, double the rate of non-STEM occupations (Business-Higher Education Forum, 2011, 2019). When considering the fastest growing U.S. occupations, 15 out of 20 require significant math, science, or technology skills. According to one study, only 6% of Americans work in a STEM field, while post graduate degrees currently fall more than 3 million short of the number demanded by the US job market (Noonan, 2017). This has spurred political action from the US government. In 2001, then-President Barack Obama's Presidential Council on Science and Technology (PCAST), a group of advisers made of scientists and engineers, was rechartered to recommend STEM policies designed to strengthen our economy and maintain our science and technology advantage. In a report on K-12 STEM education, PCAST suggested that more than one million new STEM graduates would need to be created by 2023 to maintain U.S competitiveness (Olson & Riordan, 2012). In his following state of the union, President Obama reiterated this call for 1 million STEM graduates and announced another three billion dollars in STEM education funding (Kahn, 2015; Obama, 2011). The Trump Administration also reiterated U.S. executive support for

STEM education and allocated an additional $200 Million to fund computer science education grants (Granovskiy, 2018). Neither administration was the first to emphasize STEM education; George W. Bush proposed the American Competitiveness Initiative in 2006 to fund STEM research and provide grants for innovative primary and secondary school STEM education initiatives (Domestic Policy Council, 2007). While political will has been engaged to solve the problem of creating STEM graduates, STEM job vacancies still abound (Deming & Noray, 2018).

With the growth of STEM occupations outpacing the number of STEM graduates, the National Mathematics Advisory Panel felt it was important to state that U.S. science and technological prowess was intimately tied to student exposure to quality STEM education (NMAP, 2008). Quality STEM education, as defined in the STEM Education Innovation Act (Honda, 2012), should strengthen students' skills in STEM. However, these efforts to improve STEM preparedness are often thwarted by the continuing relatively small numbers of potential STEM students. One study indicated that less than half of potential college students showed interest in STEM careers (Mattern et al., 2014). For certain career fields (e.g., engineering and math) the numbers are even worse: only 7% of U.S. bachelor-seeking students major in engineering or mathematics. Additionally, matriculation rates in STEM remain low, as fewer than half of those who declare STEM majors graduate with a STEM degree (Chen, 2009; National Academies, 2016).

While STEM degrees serve as a critical road marker for the modern American economy, the trajectory of STEM degree completion has often been represented as a narrowing, or 'leaky' pipeline or pathway (Metcalf, 2010; National Academies of Sciences, Engineering, and Medicine, 2016, 2017; National Research Council, 2011). A report by Irwin et al. at the National

Center for Education Statistics showed a steep decline in the overall numbers of students from early high school to STEM degree completion, as seen in Figure 1.3 (2021). Attempting to keep students engaged in STEM continues to be a challenge.

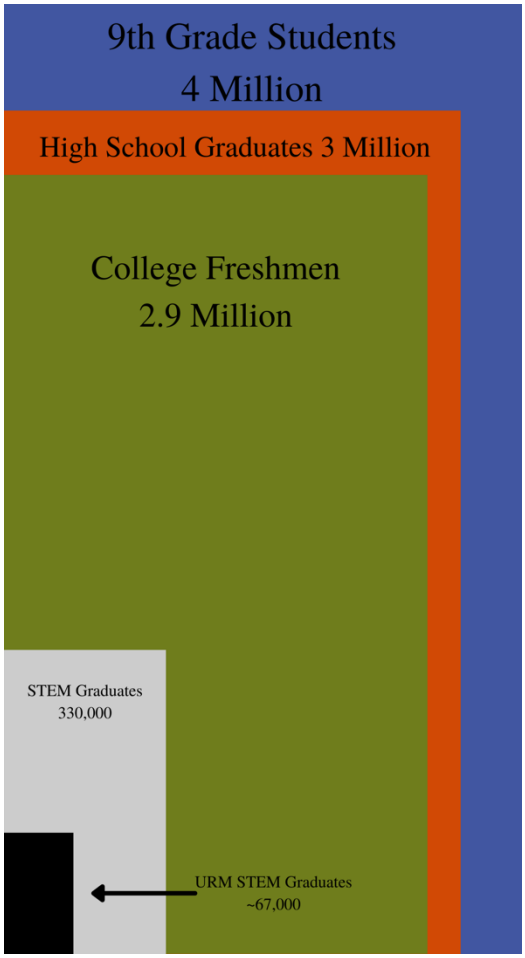

Figure 1.3. Visual Representation of High School to STEM Degree Completion for US Students from 2020 estimates

One area of primary concern has been the lack of improvement in recruiting underrepresented students to enter STEM pathways. As the baby boomer generation has aged, the mostly white, male STEM workforce has also aged. The shortfall in U.S. STEM graduates has been predominantly made up by non-U.S. workers, particularly from India, China, and Korea (The National Academies, 2014). In the last 10 years, non-citizens make up nearly all the growth of the U.S. STEM workforce (Hira, 2019). While this strategy may have limited STEM

vacancies, this reliance on foreign STEM professionals is not sustainable given the declining number of international students choosing to study in the U.S. To increase the number of skilled STEM workers in the U.S. novel and effective engagement with STEM at the primary and secondary stages of education is essential, as is increasing interest in STEM among American students, particularly those currently underrepresented in STEM careers. This culminates in the question: what are the factors that influence a student to choose a STEM major and then proceed to a career in a STEM discipline?

Underrepresented Group STEM Participation

America's demographic profile has changed quickly over the last 30 years. The number of people of color in the United States has continued to grow at a faster rate than that of White people. As of the 2010 census, people of Hispanics or Latin@ origin are the fastest- growing and largest non-White ethnic group in the United States and represent 16% of the population, while Black people represent another 12% (Census Bureau, 2010). As of 2008, people of color accounted for one third of the population and are expected, when taken collectively, to be the majority group in the U.S. by the 2040s. Children of color are projected to account for 62% of school-aged children by 2050 (Census Bureau). By 2025 the U.S. population is expected to be 21% Hispanic, 58 % White, 12% Black, 6% Asian, 1% American Indian, 1% Pacific Islander, and 2% other (Census Bureau). These projections show that students in our schools are becoming increasingly diverse.

These dramatic shifts in population have not occurred at the same rate in the numbers of people of color participating in the STEM fields. Groups considered to be underrepresented in STEM are women, Black, Hispanics/Latin@, Native American, Pacific Islander and Alaskan native peoples (National Center for Science and Engineering Statistics [NCES], 2019). Women

comprise the largest underrepresented group in STEM and represent 50% of the population but only 19% of science and engineering fields. The numbers for ethnic minorities are worse. While Black people represent 12% of the U.S. citizenry, they only account for 3% of STEM professionals; similarly, Latin@ people are 16% of the population and represent 4% of U.S. STEM professionals (NCES, 2019). Expanding access to STEM will create opportunities for those traditionally underrepresented in the STEM fields while also creating opportunities to improve the overall economic status of these groups (National Academies, 2011).

Diversity brings varying approaches and lenses to solving the problems that we face as a nation (National Academies, 2011). However, despite the advantages of having a diverse STEM workforce, there are several reasons why underrepresented groups (URGs) do not pursue STEM fields. Among them are lack of access to quality science education, negative stereotypes and stereotype threat, discrimination, poor prior performance in school, lack of support from teachers and families, and lack of role models and mentors (National Academies, 2011).

Another explanation for the low representation of underrepresented groups in STEM is the lack of familiarity between the experiences of STEM professionals and students' lived experiences (Costa, 1995; Phelan et al., 1991, Reiss, 2009). The failure of science education reform initiatives and policies to consider sociocultural aspects contributes to the lack of underrepresented peoples on STEM pathways and in STEM careers (Russell & Atwater, 2005). Science education reforms that foster a sense of science identity for diverse student populations are a fruitful area of research and science identity construct may shed light on how underrepresented students make the choice to enter or not enter STEM careers (Carlone & Johnson, 2007).

Finally, the lack of STEM self-efficacy plays a significant role in the STEM career choice of underrepresented groups (e.g., Mexican Americans in Navarro et al., 2007) and was an expanded focus of this study, which gathered information on multiple underrepresented groups. Students with high science self-efficacy tend to perform better academically and are more likely to translate that confidence into long-term goals of majoring in STEM fields and becoming employed in STEM careers.

Examining Outreach Activity Participation as a STEM Indicator

STEM pathways represent the development of students from early education through college, with the final result of becoming a STEM professional. Students have a variety of influences on this journey, from STEM experiences with parents, participation in out-of-school STEM activities, and perhaps most influentially, their time spent in the classroom. Understanding the mechanisms that cause students to persist or leave these pathways has been the focus of a large body of research; factors such as race, gender, parental engagement, interest and attitudes, school achievement, teacher expertise, and school type have all been studied as potential factors in influencing student STEM career intent, or whether students stay in or exit the STEM pipeline (Beede, Julian, Khan et al., 2011; Cannady et al., 2014; Maltese, 2008; McLean, 2015; Strutchens et al., 2010). The choices students make on the road to high school graduation and then a college degree make investigating STEM persistence during this period critical (National Research Council, 2012; Roach, 2006; Tai et al., 2006).

Student achievement in STEM has become an area of intense interest for researchers, particularly of students at the post-secondary level. Post-secondary institutions often serve as the last opportunity to engage students to consider a career in STEM, so resources from the local to federal levels are increasingly applied there to increase student STEM participation. However,

one study that examined measures of student achievement and interest in STEM from the secondary to the post-secondary level concluded that student interest and attitudes toward STEM were more important to STEM career intent and persistence than achievement in math or science coursework (Maltese, 2008). These results suggest that student interest and attitudes are factors that may influence whether students persist or exit STEM pathways. One specific aspect of Maltese's study was suggested but unexplored analysis of how out-of-school activities designed to inform and guide students to STEM careers influence their decisions to pursue those types of careers in the future. These activities, outside the classroom but ideally connected to STEM content explored in school, are a part of the collection of experiences known as STEM outreach (Vennix et al., 2018).

Student Self-Efficacy

Albert Bandura's conception of self-efficacy (1977) has been examined since 1977 and expanded over the years to include several sub-concepts such as science self-efficacy. Science self-efficacy is one construct that has been shown to influence interest in STEM and STEM career intent. Science self-efficacy refers to one's confidence or belief in their ability regarding science related activities (Britner & Pajares, 2006). Students who have higher science self-efficacy tend to have greater interest in science and are more likely to pursue science related careers compared to students with low science self-efficacy (Britner & Pajares). When a student has higher levels of self-efficacy in STEM they are more likely to remain on STEM pathways to a STEM career (Pajares, 2005; Schunk & Pajares, 2002; Simon et al., 2015). Lent has published several seminal works in science self- efficacy related to predicting STEM career choice and persistence in STEM majors (Lent et al., 2005; Lent, Lopez, et al., 2011; Lent, Miller, et al., 2013; Lent, Sheu, et al., 2008). Science self-efficacy, in addition to other sociocognitive factors,

has been shown to have direct and indirect influences on science interest and STEM career intent (Lent et al., 2008).

The term self-concept refers to the general beliefs a person may have about a subject area (Weiten et al., 2012). Like self-efficacy, self-concept has been examined as a factor of STEM persistence (Nagy et al., 2006; Guay et al., 2003; Skaalvik & Skaalvik, 2002). The similarity in the terms and how they have been researched can create confusion, so in this study the term self-efficacy will be used to discuss both factors. Also, of note for this study, additional demographic factors such as race and sex that have been previously shown to have a relationship with STEM self-efficacy and STEM career intent will be examined, since in populations traditionally underserved in STEM fields it has been shown that these students have lower levels of self-efficacy and participate at lower levels in STEM careers (Byars-Winston, 2006; Nauta & Epperson, 2003).

Purpose of the Study

The purpose of this study was to identify the factors that predict students' STEM self-efficacy and STEM career intent, two important aspects of STEM persistence. The relationship between these factors and a multitude of variables was explored by measuring the potential relationship of these factors using multilevel models for STEM self-efficacy and a student's intent to major in a STEM-related area, respectively.

Research by Maltese (2008) examined student achievement and participation in STEM and concluded that while there was a relationship between achievement in science and math and STEM persistence, student attitudes toward STEM and their own evaluation of their STEM self-efficacy were more likely predictors of STEM degree persistence. As stated previously, among these factors, out-of-school experiences serve as a contextual influence on STEM persistence.

However, while mentioned, out-of-school experiences were not included as a factor of analysis in Maltese's study. This research was intended to examine the relationship between out-of-school experiences, STEM self-efficacy, and STEM persistence. Examining these out-of-school experiences is critical since prior research has shown that formal education environments have the potential to keep students off STEM pathways before they even experience what potential a STEM career might hold (Banilower et al., 2013).

This research is also intended to serve as a basis to influence how out-of-school activities are developed and funded, and potentially help parents and students select out-of-school experiences that will aid their choice to persist on or exit STEM pathways. Ideally this research will add to the literature examining STEM persistence and aid in development of more impactful STEM programming.

Significance of the Study

STEM business and industry organizations have implemented initiatives to increase the pool of applicants in the STEM workforce, while governmental intervention has led to changes in educational policy and funding priorities. Given the levels of support from tax-funded initiatives, citizens have a vested interest to ensure that funds for STEM-related education are productive. Determining the association of out-of-school STEM experiences, student self-efficacy, and student persistence will allow local and federal governments to better fund quality STEM initiatives and build cost-effective models of STEM workforce development.

Many of the studies to date on the factors that impact STEM self-efficacy and STEM career intent have not incorporated multiple demographic and contextual factors, limiting our ability to understand the contributions of the myriad of factors involved in the formation of STEM self-efficacy and STEM major intent, which leads directly to the choosing a STEM

career. This study will directly address this limitation. Second, because this study comes from a body of students who have been repeatedly measured over several years, results from this study can inform future analyses of students who progress through outreach efforts towards the STEM workforce.

Additionally, this study examines a substantially larger number of students that are underrepresented in STEM compared to the U.S. population, which will allow for conclusions to be found relating specifically to the relationship of underrepresented students and potential STEM career intent. An increased understanding of STEM self-efficacy and STEM career intent could lead to an increase in the number of students majoring in STEM fields, thereby supplying the scientific and technological workforce required by the 21st century U.S. economy.

Research Questions

1. What are the factors that influence student STEM self-efficacy?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and STEM self-efficacy?
    b. What is the relationship between student level factors (e.g., race, gender, and age) and STEM self-efficacy?
    c. Controlling for student-level factors, what is the relationship between program-level factors (program type, length, etc.) and STEM self-efficacy?
2. What are the factors that influence student intent to major in STEM fields?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and intent to major in STEM fields?

b. What is the relationship between student-level factors (e.g., race, gender, and age) and intent to major in STEM fields?
c. Controlling for student factors, what is the relationship between program-level factors (program type, length, etc.) and intent to major in STEM fields?

Conceptual Framework

In addition to the work of Bandura (1991), this study uses Social Cognitive Career Theory (SCCT) (Lent et al., 1994). This framework suggests that the distal goals of career intent and career choice are mediated by self-efficacy and outcome expectations. The framework also suggests that multiple factors influence self-efficacy and career intent. These factors include demographic characteristics such as race and sex, contextual factors like socioeconomic status, and informal learning experiences. While SCCT suggests there are pathways that directly and indirectly affect career intent, all these pathways are mediated by self-efficacy. This makes the SCCT framework ideal for studying STEM pathway trajectories and career intent.

S-STEM Survey

The Student Attitudes toward STEM (S-STEM) survey was conducted by North Carolina State University from 2011 to 2016 (Unfried et al., 2015). The S-STEM is representative of students participating in STEM Outreach across the state of North Carolina. S-STEM Survey was designed to increase understanding of the relationships between students' STEM self-efficacy, STEM major intent (and correspondingly career intent), and future performance in STEM coursework, while also examining other demographic and experiential factors. The S-STEM Survey was developed and administered to over 10,000 students across North Carolina. A middle and high school version of the instrument was developed for 6th through 12th grade students, while 4th and 5th grade students were measured in a separate instrument. For the

purposes of this study, the middle and high school version will be used. The S-STEM data set is ideal for exploring the factors that influence and predict STEM self-efficacy and STEM career intent since it contains several constructs related to these variables. An examination of this data set sheds light on the pathways in and out of STEM fields and the development of science and math interests over time.

Research Design

This study will utilize multilevel modeling (MLM) to determine the factors that predict student science self-efficacy and student STEM career intent. MLM is a sampling technique that accounts for stratification, clustering and unequal probabilities of sampling (Raudenbush & Bryk, 2002). It is useful for survey data that are not obtained by simple random sampling, but instead are stratified by groups, in this case outreach programs, as the primary sampling unit and students as the unit of interest, as is the case with the S-STEM Survey. Failing to account for the clustering and stratification will likely result in biased estimates of the standard errors and increased likelihood of Type I error (Raudenbush & Bryk, 2002).

Key Definitions

STEM Outreach. Out-of-school experiences that students can have before or after school, or during the summer. This could include STEM clubs, participation in science fairs, or participation in STEM summer programs.

Out-of-School Learning. Structured activities that occur outside of the formal classroom (Dierking & Falk, 1994). Often used interchangeably with informal learning though there is some debate as to whether out-of-school learning should be categorized as two distinct categories of informal learning and non-formal learning (Eshach, 2007).

Self-Efficacy. One's belief about their ability to accomplish specific tasks (Bandura, 1986). Sometimes used alongside self-concept. In this study, self-efficacy equates to a student's self-concept and self-efficacy.

STEM. "The academic and professional disciplines of science, technology, engineering and mathematics." (The America Competes Act of 2010, P.L. 111-358, Section 2) Also an acronym for Science, Technology, Engineering, and Mathematics.

STEM Persistence The decision to pursue and remain on a STEM pathway leading to the eventual establishment of a STEM career.

STEM Career Intent. The intent or goal action to major in a STEM field with the goal of performing in a STEM career (Britner, & Pajares, 2006).

STEM Pathways. A STEM pathway (or the STEM pipeline) is the development of a STEM professional from entering education to becoming a STEM professional. This includes the points where students enter and leave the pathway and can be used to describe the perceived lack of STEM professionals in the modern workforce (Malzahn, 2013; Gerlach, 2012; NGSS, 2011).

Chapter Two: LITERATURE REVIEW

An examination of the factors that influence STEM self-efficacy and STEM career intent is the purpose of this study. Earlier research has focused on the factors that influence student interest in STEM; these factors include race, gender, sex, socioeconomic status, and familial support (Jones, 2010; Luzzo & McWhirter, 2001; Roach, 2006). However, the study of these factors has generally focused on increasing interest in STEM without making direct connections to the more distal goals of STEM persistence and career intent. This study addresses this gap in the literature and informs STEM education policy, particularly as it relates to increasing student access and exposure to STEM. This includes formal spaces like the classroom, and those less well understood like out-of-school STEM experiences. By studying the factors influencing STEM self-efficacy and STEM career intent for students exposed to outreach efforts their effectiveness can be understood and a predictive model can be developed.

The structure of this literature review begins with an overview of the historical perspective on STEM education in the United States, followed by a description of recent STEM education reforms and the federal policy for STEM. Next, an investigation of the STEM Pipeline model and STEM persistence will be conducted. Then, a discussion of self-efficacy and its framing within STEM and Social Cognitive Theory and Social Cognitive Career Theory (SCCT) will be used to examine the factors that predict student interest in STEM and intent to pursue STEM as a career.

Development of U.S. STEM Education

In the wake of World War II, the United States was universally recognized as a superpower due in no small part to the dominance of American industry and technological prowess (Gonzalez & Kuenzi, 2012). As is often the case, war proved to be the catalyst for efforts that advanced STEM through investments in military research and the creation of STEM government jobs (Gonzalez & Kuenzi, 2012). Taken on their own, these advancements in military technology improved U.S. standing economically; it was post-war efforts, however, that focused on formalizing the American approach to prioritizing the role of STEM education. The passage of the National Science Foundation Authorization Act created the National Science Foundation (NSF) in 1950. NSF was intended to "initiate and support basic scientific research and programs [and] to strengthen scientific research potential and science education programs at all levels" (Gonzalez & Kuenzi, 2012, p. 31). While initial efforts focused on supporting doctoral STEM students, NSF also engaged in K-12 educational initiatives through teacher institutes to improve STEM education (Gonzalez & Kuenzi, 2012). However, when the Soviet satellite Sputnik was surprisingly and successfully launched in 1957 the U.S. government and American society was jolted into a more proactive role in STEM education. The possibility of Soviet dominance of space was directly linked to a deficiency in American STEM education due to "an insufficient proportion of our population educated in science, mathematics, and... trained in technology" (Gonzalez & Kuenzi, 2012, p. 32). Following Sputnik, the National Defense Education Act of 1958 was passed, creating the first federal student loan program designed to promote the pursuit of STEM degrees (Collins, 2011).

While a trickle-down effect was felt in K-12 schools, the majority of federal action in education had remained at the post-secondary level. The passage of the 1965 *Elementary and*

Secondary Education Act (ESEA), considered by most to be the most impactful legislation related to education in U.S. history, was an inflection point in this strategy. The ESEA established federal funding for local K-12 programs and was the first attempt to insist that schools maintain certain standards of educational achievement (Gonzalez & Kuenzi, 2012), though it is important to note that ESEA strictly forbade the creation of a national curriculum. Additionally, none of the original six sections of the Act nor the more recent seventh section originally included STEM-specific goals or initiatives. However, two recent reauthorizations of the ESEA, the *No Child Left Behind Act* of 2001 (NCLB, U.S. Department of Education, 2002) and *Every Student Succeeds Act* of 2015 (ESSA, U.S. Department of Education, 2015) both added STEM provisions for Local Educational Agencies (LEAs) to maintain compliance with local math and science standards for funding purposes. In many states, the implementation of science goals is aligned to and guided by the Next Generation Science Standards (NGSS) and assessed from third to eleventh grades (e.g., California Department of Education, 2015). The most recent reauthorization also included permission for states to use federal funds to develop both engineering and technology assessments based on the inclusion of engineering and technology concepts in NGSS (Darling-Hammond et al., 2016).

STEM Education Reform Efforts

Between 1965 and 2013, outside of the NDEA and ESEA, several additional attempts at STEM Education reform designed to influence student persistence in STEM were initiated. The 1965 *Higher Education Act* authorized funding for students to aid in the completion of post-secondary degrees (Higher Education Act of 1965), and when reauthorized in 2005 included more than $1 billion in STEM grants (Smole et al., 2008). However, by 1983 and the publication of *A Nation at Risk* (National Commission on Excellence in Education) the crisis in STEM

education was clear; American students had low performance in science and math compared to both their European and Japanese peers and the committee suggested that the American advantage in STEM was "being overtaken by competitors throughout the world" (p. 9). The report had a direct impact in the passage of the *Education for Economic Security Act* (Knapp, 1991). EESA authorized grants to LEAs supporting teacher training in STEM. Unfortunately, results from these efforts did not lead to improved performance as measured on international assessments. While U.S. elementary and middle school students scored above average on The International Mathematics and Science Study (TIMSS), high school students were among the lowest performers in science and mathematics (Gonzales et al., 2004; Snyder & Dillow, 2011). Additional results from the National Assessment of Educational Progress (NAEP) ranked U.S. students as 17th in science, 25th in mathematics, and 14th in reading (National Assessment Governing Board, 2010). Taken together, these results led to the *America COMPETES Act* of 2007 and its reauthorization in 2011, which formally added STEM education programs to federal agencies like the NSF, the National Aeronautics and Space Administration (NASA), the National Institutes of Health (NIH), and the National Oceanic and Atmospheric Administration (NOAA), designed to enhance STEM education outcomes for U.S. students (Gonzalez, 2011). Additionally, *America COMPETES* created the National Science and Technology Council (NSTC) to evaluate the effectiveness of educational programming and eliminate unnecessary initiatives.

The majority of federally directed funding has focused on classroom initiatives designed to improve curriculum and pedagogy linked to improving U.S. scores on these national and international assessments. However, the findings show that investment in STEM education may require redirection to have the greatest impact. Another assessment administered by the

Organization for Economic Cooperation and Development (OECD) is the Program for International Student Assessment (PISA). PISA measures student levels in math, science, and reading and is administered every three years. The 2012 results rank U.S. students 21st in science and 26th in mathematics (NCES, 2012). These assessments also outline some of the achievement gaps that continue to persist in STEM education. For example, there is still a significant gap between White and Black students; private school students score better than public school students; and suburban students scored better than their urban and rural peers (Ross et al., 2012). Interestingly, students who self-reported participation in out-of-classroom STEM experiences scored higher than students that did not participate in these activities, suggesting a relationship between out-of-school STEM experiences and STEM achievement--a topic that will be explored further in this study. While policymakers in government have supported STEM education, they have not done so with a great sense of coordination. As recently as 2018, more than 250 government funded STEM programs have spent $3.4 billion on education initiatives (Sargent Jr., 2018). Three specific agencies make up 79% of federal STEM spending: Health and Human Services (HHS), the NSF, and the Department of Education (National Science Foundation, 2010). Within these agencies, three specific programs make up more than $600 million in funding and all are specifically designed to support students, teachers, and researchers' post-undergraduate degrees in STEM. HHS administers the National Research Service Award program and focuses on postdoctoral researchers, NSF awards students completing advanced degrees in STEM-related fields, and the Department of Education Mathematics and Science Partnership (MSP) provides funding for teachers to improve their STEM skills through community partnership with businesses and professional development opportunities (Kuenzi, 2008). It is important to note that all these programs are only for U.S. citizens and therefore

designed to improve American competitiveness in the global STEM economy. Two conclusions can be drawn from this federal funding data: first, that much of the federal funding for STEM is directed at students who already are pursuing STEM pathways at a point fairly late in their educational progress, and second, this funding has focused on formal educational programs. Given the importance of STEM initiatives (both implied by federal funding priorities and by statements given by policymakers) for U.S. competitiveness in the global economy, understanding both the earlier experiences of students in the STEM pipeline or along STEM pathways, and their participation in out-of-school STEM activities, are meaningful areas of research.

The STEM Pipeline

An analysis of the research into STEM education career choice will invariably lead to being exposed to the ubiquitous STEM pipeline model of student progress toward STEM careers (*Inside Higher Ed*, 2015; Cannady et al., 2014; Maltese, 2008). Gaining popularity in the 1970s, but fully articulated by Berryman (1983), the pipeline model of STEM educational pathways is built on supply-side economic theory and describes a relatively linear journey from science and math classes in school to STEM-based careers (Seward et al., 2019). The concept of the 'leaky' pipeline has taken hold as a metaphor for the loss of potential STEM workers as they flow from K-12 education to post-secondary education and finally, STEM careers (Alper & Gibbons, 1993; Metcalf, 2010). The STEM pipeline model has been around for nearly half a century and continues to be a foundational framework of both policies and practices related to impacting STEM persistence (Cannady et al., 2014). Used as both a conceptual model and a statistical tool, the 'leaky' pipeline has often defined the approach to recruiting and retaining underrepresented and underserved students in STEM (Stevenson, 2014). In this section,

literature expounding upon the conceptualization of the STEM pipeline model will be discussed. This includes both a description of how the STEM pipeline has been presented in STEM literature with a focus on the evolution of the model over time. Following this, the 'leaky' pipeline analogy will be appraised through the lens of prior research. Finally, literature analyzing the deficiencies of the model along with its alternatives will be discussed.

Modeling the STEM Pipeline

The leaky pipeline model was initially developed by the National Research Council Committee on Education and introduced to the NSF in the 1970s (Lucena, 2006). Designed to model the sequence of steps from entering a STEM academic pathway to becoming a STEM professional, it also showed the large number of STEM professionals that researchers suggested would be necessary moving into the 1980s to maintain U.S. competitiveness in the global economy. The pipeline model has also been used to explain the persistence of students in STEM, and in particular the loss of underserved students along the STEM journey (Maltese & Tai, 2011). Though some disagree on when the model becomes illustrative of a student's experiences in STEM regarding demographics, its acceptance as the de facto logic model for the movement of students from STEM experiences to careers has not been challenged (Allen-Ramdial & Campbell, 2014). While often the "pipeline" analogy depicts the secondary student-to-STEM career journey, as seen in Figure 2.1, it has been used to depict student academic progression from as early as the elementary level (Allen-Ramdial & Campbell, 2014; Cannady et al., 2014; Snyder et al., 2009).

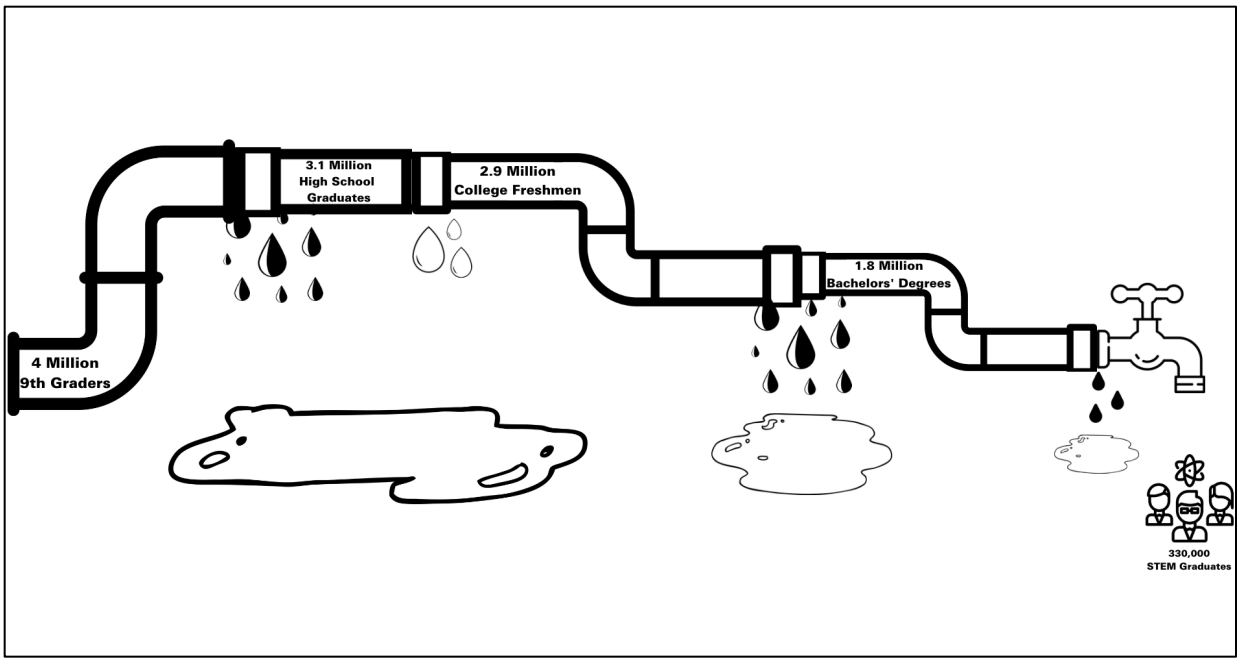

Figure 2.1 Leaky STEM Pipeline Analogy

Using the pipeline analogy, all students enter the pipeline in elementary school and correspondingly, the width of the pipe there is larger to represent the large number of students still potentially engaged in a STEM academic pathway. Over time, the pipeline narrows at junctures that simulate critical junctures along the path to a potential STEM career (Cannady et al., 2014). These junctures are seen as the source of the leakage of students away from the STEM pipeline and creates a net loss of students over time (Soe & Yakura, 2008). This net loss effect is seen at each of the junctures: fewer students exit elementary and middle schools interested in STEM than entered; fewer students leave high school prepared and interested in pursuing STEM degrees than graduate with STEM degrees; and fewer students enter STEM professions than earn STEM degrees (Cannady et al., 2014). Therefore, at the end of the pathway many fewer students have persisted in attaining STEM careers than entered the pipeline as elementary students. The linear model of the pipeline has remained an attractive tool for building retention and recruitment programs for STEM students since it is relatively straightforward to quantify the number of

students entering and exiting the pipeline at critical junctures (Harris, 2015; Soe & Yakura, 2008). Many of the predictions of STEM worker shortages have been based on this linear pipeline model, yet have proven faulty over time. Criticism of the model has thus increased and led to a new body of research on the pipeline more generally, including research into non-linear models, and specifically on the critical junctures that exist along the pipeline (Allen-Ramdial & Campbell, 2014; Cannady et al., 2014; Metcalf, 2010).

Junctures in the STEM Pipeline

While the analogy may be overused and oversimplified, research and common sense both reveal that the number of students on the pathway to a potential STEM career shrinks as time moves forward (Allen-Ramdial & Campbell, 2014). Often this 'leaky' pipeline model is defined by the important junctures that have the greatest effect along a student's educational journey (Soe & Yakura, 2008). Students who were initially traveling along the pathway to a STEM career 'leak' from the pipeline at these junctures and leave the pathway. In particular, some of the junctures are leakier than others (Blickenstaff, 2005; Cannady et al., 2014). Cannady et al. (2014) stated that these junctures coincide with events often seen as educational milestones such as receiving a high school diploma, enrolling in college, declaring a STEM major, and completing a STEM degree. Other researchers have suggested that these critical junctures occur most often during transitional phases of education: the progression from middle school to high school, graduation from secondary school, completion of an undergraduate degree and moving to graduate school and transitioning from graduate school to a STEM job (Maltese & Tai, 2011). Understanding which students are leaking and at which junctures is essential to explaining the pipeline model and reducing student loss. Indeed, there is a healthy debate to be had about which junctures are associated with the greatest net loss of students along STEM pathways. While the

transitions after secondary school have been identified as critical (Cannady et al., 2014), they are not the focus of this literature review. Instead, an examination of the junctures from elementary to secondary school will be explored.

Berryman's seminal study (1983) of minority representation in STEM degree holders posited that "the scientific/mathematical pool from which quantitative Ph.D. graduates ultimately derive first appears in elementary school...The pool reaches its maximum size prior to senior high school and subsequently declines in size" (p.14). While Berryman suggests that during high school some students may re-enter the STEM pipeline, the overall pattern is a net loss of students. Tellingly, this loss is caused both by achievement in STEM-related coursework and general STEM interest, though their impact is reflected differently among the various demographic groups. Berryman's study led to future work on underserved students in STEM and continues to serve as a useful framework to examine the leakage of students from the STEM pipeline.

Elementary and Middle School

Arguably, elementary school is where the educational path to a STEM career begins. Berryman (1983) found that elementary school students who performed well in science and mathematics courses also tended to express high interest in science and math. For many students, in a positive reinforcement cycle, high achievement in science and mathematics often leads to additional exposure to science and math, which in turn leads to increased interest in science and mathematics (Armstrong & Price, 1982; Oakes, 1990). Armstrong theorized that high-performing students were more likely to receive both subject acceleration and in- and out-of-class enrichment, which tends to provide more science and mathematics opportunities than the standard elementary curriculum. However, it is middle school that is generally seen as the first

critical juncture of the STEM pipeline, and therefore the first source of significant leaks (VanLeuvan, 2004). Using student performance data from elementary school, students begin to experience gatekeeping in specific middle grades science and mathematics coursework, limiting their exposure to additional STEM experiences (Oakes, 1990). Students with high test scores (and usually high interest) were more likely to be enrolled in advantageous mathematics courses in middle school, leading to more STEM opportunities in high school (Oakes, 1990). The clearest distinguishing course sequence was mathematics, pre-algebra and algebra, in which high-performing students were overwhelming enrolled, while lower-performing students, who were also perceived by teachers and administrations as having lower STEM interest, were more likely to be assigned to remedial/regular mathematics courses (Oakes, 1990). This is critical to note as researchers have found that taking algebra in middle school is a key factor in distinguishing future STEM professionals from those who decide not to pursue STEM as a career (Cannady et al., 2014; Maltese & Tai, 2011; Nicholls et al., 2010). The lack of exposure to more advanced mathematics and science courses for low achieving students only served to perpetuate their continued low interest in STEM (Oakes, 1990). A negative feedback loop was developed where low-skilled, low interest students in STEM were not given additional exposure to STEM, removing any future opportunity to develop higher-level skills or higher interest, which made them less likely to be prepared for additional positive STEM exposure. The result of this negative feedback loop increased the likelihood that these students would exit STEM pathways as they progressed in their education (Oakes, 1990).

High School

High school has been shown to be a critical juncture in the educational experiences of future STEM professionals. Though some studies have suggested that middle school measures of

STEM interest serve as strong predictors of STEM persistence into and through high school (Sadler et al., 2012), earlier studies suggested that achievement becomes more important for high school students (Berryman, 1983). Additionally, high school was found to be the last juncture where large numbers of students have an opportunity to re-enter the STEM pipeline; Hilton and Lee (1988) concluded that the number of students losing interest in STEM is nearly equivalent to those that increased in STEM interest. As in middle school, students with higher levels of academic achievement received more exposure to STEM opportunities throughout their high school curriculum (Oakes, 1990). In their study of gender differences in the prediction of STEM majors, Ware and Lee (1988) reported that high school achievement, measured by grade point average (GPA), was a predictor for STEM persistence through high school. Oakes (1990) noted that students with higher GPAs had more curricular opportunities to increase their STEM exposure; Oakes concluded that this exposure was more likely to help these students maintain higher levels of STEM interest and thus increase their likelihood of remaining in the STEM pipeline. Alternatively, students with lower levels of overall achievement were placed in remedial course work, especially for mathematics, and often guided to coursework more likely to lead to non-STEM careers (Tyson et al., 2007). Additionally, these studies found that high SAT scores and higher class rank also correlated with increased levels of persistence, particularly for white and Asian students (Maltese & Tai, 2011; Strayhorn, 2011). While for traditionally underserved racial groups this did not tend to discourage their future selection of a STEM major, women (an underserved group regardless of racial identity) who were guided towards fewer mathematics and science courses became less likely to pursue a STEM degree and less likely to be prepared for college-level academics in general.

The academic rigor of a student's high school coursework was identified by Adelman (2006) as the most critical indicator of general persistence to a college degree. While Adelman's study did not specifically examine persistence in STEM, other researchers have since reinforced Adelman's conclusions with their own data. Studies from Maltese and Tai (2011) and Tai, Sadler, and Mintzes (2006) both found that students who took a calculus-based math course were more likely to persist into a STEM degree path in college, while students who performed well in these courses had even higher rates of persistence. Another study of students in Advanced Placement courses found that they were 1.6 times more likely to persist toward a career in STEM when they received a 'B' or better in the course (Sadler et al., 2014), with increased rates for students taking combinations of these courses (e.g., physics and calculus, or biology and chemistry) (Redmond-Sanogo et al., 2016). Relationships between race and persistence were difficult to track in most of these studies as white students were generally overrepresented in the samples. It is also important to note that in these studies no determination was made of STEM degree *completion*; only the matriculation of first-year college students in STEM degree programs was explored.

Research has shown that the types of classroom experiences that high school students have had an effect on whether students stayed on or left STEM pathways (Maltese & Tai, 2011). Maltese and Tai defined classroom experiences as "the pedagogical practices, educational emphases, and achievement outcomes that students experience in their mathematics and science classes" (p.882). Students involved in hands-on learning activities and cooperative learning were also more likely to have positive attitudes toward STEM (Myers & Fouts, 1992). Piburn and Baker (1993) found a positive correlation between hands-on activities and positive STEM attitudes; additionally, student input in the curriculum, including choosing what they saw as

relevant subject material, had a positive connection to STEM persistence. Students who identified their teachers as having high pedagogical content knowledge had increased STEM attitude levels, while teacher enthusiasm for subject content was named as a significant factor for students who chose to persist in STEM (Woolnough, 1994). These experiences have been shown to have positive impacts for all students, but they are particularly important for students underrepresented in STEM (Oakes, 1990).

It is the juncture between graduation and the beginning of college that offers the greatest decline in the number of potential STEM students (Berryman, 1983; Hilton & Lee, 1988). This is important to note, as Astin and Astin (1992) found that the act of choosing a STEM major was, predictably, the most essential factor to persisting in a STEM degree. This research reinforced the results of Oakes (1990) study which revealed that choosing a STEM major positively correlated to entering a STEM career. While choosing a STEM major is prefaced on high school performance in advanced classes, end-of-course testing, and norm-referenced exams such as the SAT and ACT (Maltese & Tai, 2011; Strayhorn, 2011), declaring a STEM major by the end of freshman year was more strongly correlated to persistence than any of the aforementioned factors (Bonous-Hammarth, 2000).

An examination of the critical junctures in the STEM pipeline provides opportunities to evaluate why some points are more important than others, while also revealing the factors that influence student persistence in STEM. This examination reveals several challenges for educators and policymakers related to improving student success: mathematics and science learning opportunities are clearly critical to student success; student performance in secondary school science and math coursework correlates to college preparedness for STEM; and student attitudes toward math and science are important factors in rates of persistence. However, using

these junctures as research variables requires two important assumptions about their uniqueness in terms of correlating to STEM outcomes: that the actual number of STEM professionals who followed the STEM pipeline as currently modeled can be understood, and that these factors are unique predictors of STEM outcomes (Cannady et al., 2014). Taken together, this means that as the amount of potential STEM professionals in the pipeline increases, the more generalized the criteria for distinguishing those who will become STEM professionals from everyone else becomes; in other words, the pipeline model becomes so broad that the factors influencing persistence cannot be understood. Therefore, it is important to understand which criteria actually matter and which are not essential (Cannady et al., 2014). A deeper examination of the factors that influence STEM persistence is warranted.

Person-level Factors

Students leave STEM pathways for a number of reasons, though it is clear that some demographic groups disproportionately leave STEM compared to their peers (Berryman, 1983). Additionally, these losses occur asymmetrically even amongst these demographic groups even at the same critical junctures (Oakes, 1990). Discussion about the critical need for understanding the influence of these factors is ongoing and extensive (e.g., Beede, Julian, Langdon, et al., 2011; Maltese, 2008; Niu, 2013). As racial demographics continue to change in the United States (Museus et al., 2011), the number of women in STEM continues to increase (Espinosa, 2011), and the clear economic advantages of STEM degrees for students from low-income families becomes more telling (Carnevale et al., 2010), these factors must become better understood.

A variety of factors influence persistence into a STEM career at different levels of significance; for example, the taking of certain high school courses has been shown to be more of a factor than socioeconomic status (Schneider et al., 1998). While external factors like

qualified teachers and schools with challenging science and mathematics curricula also have been associated with persistence in STEM (Aud et al., 2010; National Assessment of Educational Progress, 2010), internal, or person-level factors such as student attitudes appear to have a critical role in STEM persistence (Connors-Kellgren et al., 2016). Particularly, attitudes towards STEM seem especially relevant in the difference between male and female STEM persistence (NSF). STEM self-efficacy, or a student's belief in their ability to perform will in STEM environments, has been shown consistently to be an aspect of STEM persistence (Soldner et al., 2012). Understanding why some students have higher levels of STEM self-efficacy is critical to understanding which students persist to STEM degrees.

Gender has been shown to be a relevant factor in leaks from the STEM pipeline, particularly at both the middle school to high school junctures (George, 2006). Beginning at the elementary level, boys and girls have roughly similar attitudes toward STEM (Baram-Tsabari & Yarden, 2011). However, George found that girls become much more likely to experience declines in STEM interest during this period; though interestingly, boys who do experience declines in STEM interest do so at much higher rates than girls (Simpson & Oliver, 1990). Toward the end of secondary school, as noted beforehand, the overall interest in STEM among both boys and girls has declined, and the gap in positive attitudes about STEM between boys and girls is over twenty times larger than it was at the beginning of middle school (Baram-Tsabari & Yarden, 2011; Oakes, 1990). Positive experiences in mathematics and science classes were a significant factor in whether or not girls were likely to choose a STEM major (Tai et al., 2007), though overall males were found to be three times more likely to choose a STEM major (Sadler et al., 2012). However, girls with higher measured levels of STEM self-efficacy were more likely to make plans to pursue STEM as a career (Nauta & Epperson, 2003). Another mitigating factor

is that many females feel discouraged from pursuing STEM because of the competitive, and often unwelcoming culture of STEM for women (Riegle-Crumb et al., 2012).

In terms of race, African American and Latin@ students are lost much earlier along the STEM pathway (Berryman, 1983; Strayhorn, 2011). For many, it begins even before school begins, as parental education and career were found to be predictors for future STEM achievement; both African American and Latin@ families have lower levels of academic attainment and socioeconomic status compared to other ethnic groups (Oakes, 1990). Regardless, researchers found that these families still recognized the value of STEM as a tool of upward socioeconomic mobility and promoted STEM experiences to their children (Carnevale et al., 2010). Students that received positive reinforcement related to the value of STEM education were more likely to take the relevant coursework for pursuing a STEM career; unfortunately, African American students lagged behind their peers in this measure (Harackiewicz et al., 2012). African American and Latin@ students are also more likely to attend schools that are less academically rigorous and have fewer opportunities for STEM experiences (Strayhorn, 2011; Zarate & Pachon, 2006). Additionally, while programs to keep African Americans interested in STEM have been promoted and deployed during the middle and high school years (DeJarnette, 2012), research has shown that elementary school might serve as the greater leverage point to create continual interest in STEM for African American students (Russell et al., 2007). The lack of early intervention in STEM for African American and Latin@ students is amplified by what is often a lack of STEM resources for these underserved students (Valla & Williams, 2012). The seminal work of Wigfield, Eccles, and others (2007) on achievement motivation found that the draining of these students from the STEM pipeline was more related to their misconceptions about STEM careers than to their ability to pursue them. Often, there is an antipodal relationship

between how African Americans, and to a lesser extent, Latin@ students, feel about STEM at an abstract level (typically positive) and how they consider STEM as a future career option for themselves (unlikely) (Downey et al., 2009; Mickelson, 1990). However, it is clear that additional exposure to STEM increases the likelihood that these students will remain on STEM pathways.

The pipeline model of STEM has been the foundation of specific efforts for underserved groups for more than four decades (Metcalf, 2010). It is often used to model the shortfall of STEM workers, which in turn leads to the claim that underserved groups can be used to fill the needs of the global STEM workforce (Herrera & Hurtado, 2011). However, policies designed using the pipeline as a framework continue to present an oversimplified solution to the issues of retention in STEM (Metcalf, 2010). For example, while California used the pipeline model to justify its decision to make all students take algebra before entering high school there was little empirical research to support the policy (Liang et al., 2012). Indeed, some research has shown that gatekeeper courses reduce the number of participants from underserved groups on STEM pathways (Maton & Hrabowski, 1995). Additionally, the proliferation of summer bridge programs for STEM was also built on the pipeline model even though the research to support their effectiveness is limited (Strayhorn, 2011). A more in-depth understanding of how underserved populations move along STEM pathways is still required.

Implications and Limitations of the Current STEM Pipeline Model

The passage of time has led to the rise of several critiques of the STEM pipeline model (Cannady et al., 2014; Maltese & Tai, 2011). Persistence of underserved groups, including

specific racial and ethnic groups along with females, has proven challenging to model (Cannady et al., 2014). The concept of one entry point and one exit point does not model the variety of experiences a student may have on their way to a STEM career (Hammonds & Subramaniam, 2003). The equal treatment of students that historically have not been treated equally is another failure of the model (Soe & Yakura, 2008). Additionally, alternate pathways or nontraditional entry points (e.g., graduate school) are not accounted for in the model. Potentially more troubling, the pipeline model treats students as non-active participants pushed along by the invisible 'pressure' that the pipeline provides, ignoring the choices and motivations of the participants themselves (Cannady et al., 2014). The pipeline model also focuses on supply, while ignoring demand, leading to the potential unemployment of individuals who choose the 'wrong' STEM career even though they complete and exit the pipeline (Metcalf, 2010). The homogenization of students that occurs in the pipeline model leads to generic fixes that ignore the underlying issues defining why some students leave STEM pathways and others remain (Cannady et al., 2014).

Researchers sensing the inaccuracies of the existing STEM pipeline model have proposed alternate conceptions of the model that would address its limitations. The pipeline as a multiple trajectory model was proposed by Cannady et al. (2014) to describe the nonlinearity of some students' journeys along STEM pathways. Allen-Ramdial and Campbell (2014) conceptualized the pipeline as a vertical tower subject to gravity and pressure changes, where negative forces (lack of academic preparation) push students downward, while positive forces (strong mentorship) create upward pressure. Soe and Yakura (2008) developed a multi-layered model (societal culture, occupational, and organizational) that theorized that occupational culture was influenced by the underlying cultures of the student along their pathways to STEM careers.

Out-of-School STEM Activities

There is little doubt that exposure to STEM provides the opportunity to increase student perceptions of STEM. Distinguishing formal STEM experiences from informal, or out-of-school STEM experiences is an important step to understanding their respective impacts. For example, students in formal STEM experiences often perceive formal activities as separate from their daily lives (Schwartz & Noam, 2007). Additionally, formal STEM experiences must fit into the structure of mandatory testing, large classrooms, and pre-defined curricular models (Committee on Prospering in the Global Economy of the 21st Century, 2007). It is the advantage of informal experiences that they can be centered around real-world experiences that relate to how students identify culturally, particularly since the deficiencies of formal STEM learning often impact underserved students disproportionately (Kleiner & Lewis, 2005). Out-of-school, or informal, experiences such as participation in a STEM outreach program, can serve to provide the support necessary to keep students who are more likely to leave STEM pathways at critical junctures in the pipeline (Tai et al., 2006). Specifically, previous research of STEM outreach programs has shown that these programs are often designed to provide the additional support to keep students on STEM pathways (Kuenzi, 2008).

The average American student has access to a wide array of analog and digital resources related to STEM, though some researchers have argued that these resources disproportionately support groups overrepresented in STEM (Gándara, 2001; Villalpando & Solórzano, 2005). These STEM experiences are informal and are provided by community organizations like Girl Scouts or the Y(MCA) or, increasingly, by U.S. colleges and universities (Swail et al., 2012). Schools of higher education are committing increasing resources to developing informal programs that will attract underrepresented students because research has shown that these

opportunities are essential for the development of students' STEM skillset and for increasing student attitudes toward STEM as a career, particularly in underrepresented students (Horn & Chen, 1998). It is estimated that students spend approximately 95% of their time *outside* of the formal classroom space, so it follows that most of what students know about STEM is learned outside of the science or mathematics classroom (Dierking & Falk, 1994; Falk & Dierking, 2010). Data from the PISA seems to support this assertion; experiential learning, hobbies (when they were STEM-related), and afterschool programs were strong predictors for high achievement on the assessment (Allen et al., 2019). Including non-OECD nations, the countries that ranked highest on the science domain of the assessment were also the countries most likely to have a wide variety of informal STEM learning opportunities (Schleicher, 2019). While the nature of the relationship between formal STEM learning activities and time spent participating in informal STEM activities is not clearly defined, the results suggested that there is a relationship between the amount of time students spend participating in informal STEM activities and their performance on standardized assessment such as the PISA (Allen et al., 2019).

Several other research studies have also found that informal STEM activities have a positive impact on student knowledge about and attitudes toward STEM. A Harvard study focused on informal programs found that competently designed after school programs help students become stronger candidates for the modern workforce (Xie & Shauman, 2004). They also found that access to informal learning opportunities were a strong predictor of students' future learning success and academic achievement. Falk and Dierking (2010) reported on a Science Center in California that surveyed visitors over a 10-year period and found that participants' self-reported understanding of STEM increased. Because of the likelihood that these students' exposure to STEM was more likely to be driven by informal experiences at pre-high

school ages, Falk and Dierking argued it validated the concept that informal STEM learning was potentially more valuable than formal experiences. Another longitudinal study of after school programs found that good programs could improve student engagement, achievement, and attitudes toward the subjects they promote, even when academic achievement was not the main focus of the program (Little, Wilmer, & Weiss, 2008). A study from the Wisconsin Center for Education Research determined that students were more likely to have positive attitudes toward and remain engaged with subject matter when they were given opportunities to develop their skills in real-world scenarios and had opportunities to experience a diverse array of topics to find their interests (Mahoney et al., 2009). The results of this study implied that specific programs, like those that focus on STEM, could provide these opportunities.

The clear need for additional informal STEM experiences has led government agencies, academic organizations, colleges and universities, nonprofits, and the business sector to attempt to address the need through intensive STEM experiences designed to increase student attitudes toward and knowledge about STEM (Fleming, 2011). As of 2006, in the U.S., more than 8 million students attend after school programs (Blau & Currie, 2006). An evaluation performed by the Afterschool Alliance suggested that STEM out-of-school experiences led to direct STEM-specific gains. Students in these programs showed increased attitudes toward STEM fields and careers; higher likelihood to pursue STEM as a career; and increased STEM knowledge and measurable skills (Afterschool Alliance, 2014). However, future research was needed because while the data was promising, the research did not lead to a model that predicted the successful aspects of an informal STEM learning experience.

A variety of informal STEM outreach activities have been employed to improve STEM self-efficacy and student persistence into STEM careers; this includes experiences in STEM

clubs (Dabney et al., 2007; Kier et al., 2014); participation in STEM competitions (Miller et al., 2018); STEM summer camps (Kong et al., 2014; Roberts et al., 2018); museum experiences (VanMeter-Adams et al., 2014); and college and university-led outreach (Perna & Swail, 2001). Dabney and others (2012) examination of the connection between informal STEM activities and STEM interest found that students who participated in such activities were 1.5 times more likely to choose a STEM major in college, and suggested this may have been due to an increase in STEM self-efficacy and measures of social acceptance. Using SCCT as a framework, Zhang and Barnett (2015) found that participants in a STEM-based career club experienced changes both to their measures of self-efficacy and their intent to major in a STEM field, though most attributed any change to interactions with parents and adults outside the program. Another study by Akca et al. (2018) found that participation in STEM clubs positively impacted student attitudes toward STEM, though they could not discern if certain types of clubs were more impactful than others. Public spaces such as libraries and museums also play a role in these out-of-school experiences, particularly if they focus on engaging students in topics relevant to their cultural backgrounds (Honma, 2017).

Out-of-school efforts driven from the college and university level enroll more than two million students each year (Perna & Swail, 2001). The majority of this outreach is at the K-8 level and supports goals such as increased college awareness and improving academic skills (Perna & Swail). These programs often target underserved groups. For example, a study by Lane et al. (2020) showed that a university-led STEM enrichment program could positively influence the development of a student's STEM identity. While not a direct measure of self-efficacy, prior research has shown links between STEM identity and STEM self-efficacy. Results from an interdisciplinary program and a subject-specific program in earth science show that a variety of

program types can also positively influence STEM career intent (Carrick et al., 2016; Kim, 2016). These interventions can also be implemented along differing timescales; one study showed similarly designed experiences, delivered as one day programs versus multi-day programs did not create a significant difference in the programs' measured outcomes (Dillon et al., 2016). In terms of program logistics, a study of outreach interventions in the U.S. named a generalized set of features that were prevalent in programs rated as effective (Schultz & Mueller, 2006). These effective features were: strong academic preparation; balanced academic and social support structures; early intervention; the involvement of family members in the program; college admission counseling; long term support for participants; systemic reform of student matriculation guidelines; and financial support. However, the lack of consistent focus in outreach interventions has made comparison across programs difficult and continues to be an obstacle to developing guidance for those that seek to implement successful outreach programming (Perna & Swail, 2001).

Self-Efficacy

Self-efficacy is generally understood as the belief or confidence a person maintains related to specific actions or tasks (Bandura, 1997; Pajares, 2005); this is particularly applied to academically related subjects (Bong & Skaalvik, 2003). Compared to self-concept, self-efficacy focuses less on how individuals feel about their skills and more on what an individual believes they can do with the skills they possess (Bong & Clark, 1999). An individual with high levels of self-efficacy in a defined subject area is generally more willing to engage in activities related to that subject or to believe that they can successfully complete a goal related to that subject. In particular, for academic tasks these skills apply to completing goals at relevant levels, i.e., goals specific to reading at the first-grade level or to high school

science for secondary students (Zimmerman & Schunk, 2001). Self-efficacy has also been thought to be positively correlated to motivation in students (Bandura & Locke, 2003), and therefore has tremendous potential in explaining student achievement, career interest, and eventual career choice (Eccles, 1994; Lent et al., 1986). A common theory of action in education is that of the student who thinks that they will perform well in a class and then earns grades consistent with their self-efficacy beliefs, assigns any failures not to a lack of intelligence, but to deficient effort (Zimmerman, 2000). In contrast, students with low self-efficacy beliefs related to particular subjects and tasks tend to make lower grades consistent with those beliefs, even when their measures of intelligence suggest they should be performing better. Self-efficacy, as an affective quality, has especially been a focus of research for underserved students and is often tied to the achievement gap between those students and their White peers (Forsyth et al., 2007).

Albert Bandura's *Social Foundations of Thought and Action* (1986) expressed the concept of individual control over the choices they make; these choices are meant to create positive progress for individuals, are self-regulated, and free from the influence of environmental factors (Bandura, 1986). Bandura referred to this concept as self-belief, which influences our behaviors and actions (1986). By studying an individual's self-beliefs, predictions about their actions could be made related to how their beliefs guide what they do with their skills.

The effects of self-efficacy have been studied in a variety of situations. Schunk and Swartz (1993) examined self-efficacy in writing performance and found that individuals participated more frequently in writing tasks that they felt confident doing while avoiding tasks that made them feel less confident. In another study, efficacy beliefs were correlated to

the amount of effort children were willing to exert on challenging activities and their level of perseverance when faced with failure (Schunk & Hanson, 1989). Both studies reinforced the concept of predictable behaviors based on an individual's self-beliefs, beliefs that determine how individuals manage their knowledge and skills (Schunk & Pajares, 2002). Self-efficacy is also related to student achievement; student beliefs and perceptions have been shown to affect academic growth and development (Bandura, 1997).

Self-efficacy also has a role in the factors that influence mathematical problem solving. Achievement in mathematics improved with higher levels of self-efficacy, along with non-achievement related factors like attitudes toward math in general (Pajares & Miller, 1994). In the same study of college undergraduates, student self-efficacy beliefs were better predictors of mathematical problem solving and academic achievement than self-concept, perceived usefulness, prior math experiences, or gender. Additionally, there was interaction between self-efficacy and the other factors, further demonstrating how Bandura's theory explains how self-efficacy changes the choices and actions individuals choose; in general, these studies reveal that with greater self-efficacy individuals are willing to exert greater effort at tasks.

STEM Self-Efficacy

STEM self-efficacy is an extension of self-efficacy and typically associated with STEM-centered academic pursuits (e.g., science and mathematics) and refers to one's belief in their ability to accomplish STEM-related academic tasks; this has been especially true of math and science self-efficacy (Britner & Pajares, 2006; Lent et al., 2005). Previous research has shown that positive science self-efficacy is associated with achievement in STEM at the secondary and collegiate levels (Betz, 2004; Betz & Hackett, 1983; Lent et al., 1986; Taylor &

Betz, 1983). For undergraduates, science self-efficacy has been linked to increased persistence in STEM (Perez et al., 2014). Science self-efficacy has also been shown to be a predictor of academic achievement regardless of academic ability (Komarraju & Nadler, 2013). Math self-efficacy has also been connected to academic achievement in STEM coursework; therefore, math self-efficacy has been used to more broadly evaluate STEM self-efficacy. For example, students with high levels of math self-efficacy also had increased levels of STEM persistence (Wang & Degol, 2013). Self-efficacy also influences an individual's future career choices and goals related to STEM (Eccles, 1994), and higher levels of self-efficacy may be a predictor in STEM persistence (Ormrod, 2006).

Self-efficacy also has a relationship with race and ethnicity, and the study of STEM self-efficacy. It has been one method of addressing the retention of underserved students in STEM and a fertile ground for research on persistence (Dietz et al., 2002). Bandura attempted to explain lower levels of self-efficacy by highlighting the differences in learning environments and socioeconomic status between Black and White students (1997). Gwilliam and Betz (2001) examined three measures of science and math self-efficacy between Black and White undergraduates and found that race was a predictor of STEM persistence when self-efficacy was a factor. White students were more likely to have higher levels of STEM self-efficacy than their Black peers. In particular, Black women were more likely to choose non-STEM majors when they had low levels of STEM self-efficacy (Lewis, 2003). Further research into the relationship of race and ethnicity, and STEM self-efficacy is still necessary. Designing STEM experiences that enhance STEM self-efficacy may encourage higher levels of STEM career intent and increased levels of persistence for underserved groups (Lewis, 2003). However, while self-efficacy is considered a short-term construct that is often

measured employing a pretest/posttest research design, STEM career intent is a more abstract concept that develops longitudinally (Lent, Brown, Brenner, et al., 2001). Together, these concepts provide the foundation for Social Cognitive Career Theory.

Theoretical Framework of This Study

The purpose of this study was to understand the how and to what extent a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) predict student science self-efficacy. This study draws on Social Cognitive Career Theory (SCCT) proposed by Lent, Brown, and Hackett (1994). This framework suggests that the longitudinal goals of career intent and career choice are mediated by self-efficacy and outcome expectations. The framework further suggests that several factors influence self-efficacy and therefore career intent. This study utilized the SCCT model to better understand student attitudes toward STEM by examining their STEM interest and future career aspirations. Of particular interest was exploring the various sources of influence for STEM choice-making with a focus on person-level variables. During STEM outreach programs, participants develop and establish their beliefs, values, and expectations for success in STEM. In addition to the SCCT model, Eccles's Expectancy-Value Theory model will also be used to help explain how participants developed an interest in STEM careers. For this model, sources of inference for STEM choices include external, social, and personal influences. Guided by SCCT, personal variables influenced participants' motivation in choosing STEM coursework. During the establishment of beliefs, values, and expectancies in STEM, outlined in the Expectancy-Value Theory, participants developed aspirations toward choosing a career in STEM.

While many of the studies on the factors that influence science interest and STEM career intent only study variables in isolation, there is a need to examine several factors simultaneously in order to provide a more comprehensive picture of the STEM career intent development process and to provide more predictive power. Additionally, many of these studies occur at the college level, after a student has already chosen a STEM career, and therefore seek to examine persistence or attrition. There are far fewer studies that examine STEM career intent at the secondary level, and few studies go beyond the analysis of demographic and achievement factors such as GPA and standardized test performance. Thus, by examining several factors simultaneously in order to determine which factors predict science self-efficacy and STEM career intent and to what extent they predict them, this study helps fill this gap in the literature.

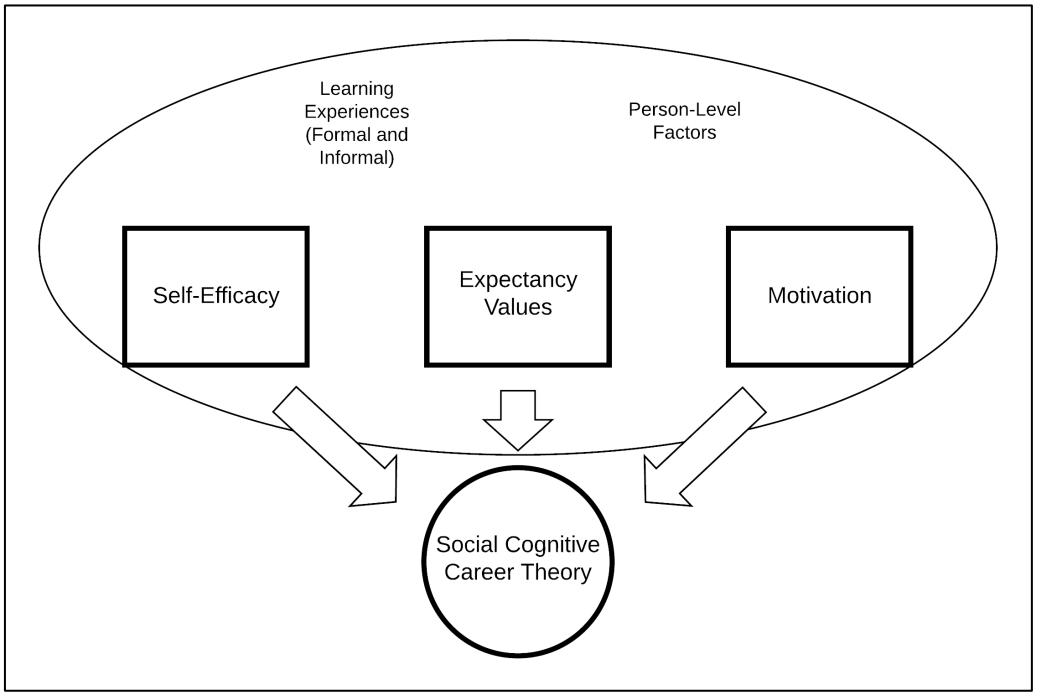

Figure 2.2 Interaction between Expectancy Value Theory and Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT)

Social Cognitive Career Theory (SCCT) is an extension of Social Cognitive Theory (Bandura, 1986) that explains how young people make decisions about, develop interest in, and explain how they perform in specific careers (Lent et al., 1994). As a theoretical model, SCCT is composed of three social cognitive components: self-efficacy, outcome expectations, and goals. Though the models of SCCT focus on particular academic and career outcomes, the components exist in a state of overlap by design (Lent et al., 2013). SCCT is the theoretical lens that looks at the interaction between personal factors (intrinsic motivation, affective dimensions, demographics), behaviors (choices and actions), and an individual's environment (Bandura, 1989). SCCT builds on Bandura's Social Cognitive Theory (SCT) of how individuals regulate their behavior through internal processes, beliefs and expectations, and how in turn, these drive human behavior. The expectations that occur from this make up two of the social cognitive components: outcome expectancy and self-efficacy (Bandura, 1989). As seen in Figure 2.2, SCCT posits that the cognitive dimensions (e.g., self-efficacy, outcome expectations, and goals), the environmental factors (e.g., educational climate, family support, socioeconomic status), and behaviors (whether educational or career-related) interact in a reciprocal way to support or block each of the other dimensions (Lent et al., 2013). Therefore, interest development and goal progress will occur during activities where individuals have higher self-efficacy and for which they expect more favorable outcomes. Person inputs and environmental conditions directly impact student learning, which then impacts self-efficacy and outcome expectations. These factors affect student academic and career interests and influence student persistence.

SCCT focuses on social cognitive person variables (self-efficacy, outcome expectancy, and goals), and on how these variables interact with other aspects of an individual and their environment (gender, ethnicity, social factors, and environmental barriers) to help shape the course of their career choices (Lent et al., 1994, 2000). Therefore, self-efficacy and career interest are not the only factors that influence career choice. Lent et al. (1994, 2000) structured SCCT with two complementary levels of theoretical analysis, one based on social cognitive factors, while the second level examined person-level factors like gender or ethnicity.

STEM Career Intent

The SCCT framework also encourages the exploration of external supports and how they impact career choice and STEM persistence. The major studies have found a positive correlation between STEM self-efficacy, outcome expectancy, STEM career interest, and STEM persistence (Lent et al., 2008). Byars-Winston et al. (2010) examined the relationship between STEM self-efficacy and outcome expectations and student STEM degree intent. Using SCCT, Shaw and Barbuti (2010) examined STEM persistence for first-year college students and the impact that gender, socioeconomic status, ethnicity, and first-generation college-student status had on their decisions to remain in STEM majors. By their third year of college, 59% of the students had left STEM majors. The researchers found that the most significant variation was in ethnicity, as American Indians/Alaskan Natives, Hispanics, and Asian/Pacific Islander students had the highest rates of attrition. This lack of persistence in post-secondary education contributes to the “leaky” pipeline analogy, used to describe the declining pattern of underserved students majoring in STEM fields (Morgan et al., 2013). Although research has explored the social cognitive factors of SCCT, further research to examine contextual variables of the model are ongoing.

Researchers of STEM career intent suggest that interest in science has a significant impact on choosing a STEM career when interest is cultivated at younger ages (Wang & Degol, 2017). Additionally, exposure to STEM careers has also been shown to positively influence STEM career interest (Beggs et al., 2008). Science self-efficacy has also been shown to predict STEM career intent (Britner & Pajares, 2006). Research has also shown that STEM career intent can be positively influenced by exposure to mentors and engaging STEM content when students repeatedly participate in STEM outreach programs (Ricks, 2006). STEM outreach programs expose students to STEM careers through experiential learning that does not traditionally take place in formal school environments. Several studies suggest that informal STEM outreach positively influences STEM career intent (Farmer, 1997; Packard & Nguyen, 2003). Additionally, post-elementary science interest has been shown to predict STEM career intent (VanLeuvan, 2004). Wang (2012) used SCCT to understand how high school students select undergraduate STEM degree programs. The results indicated that the largest impact on STEM major entrance was STEM career intent, which was correlated to math academic performance, math self-efficacy beliefs, and participation in STEM coursework. While research exists on STEM persistence at the college level, less focus has been placed on STEM career intent for secondary students.

Summary

The purpose of this chapter was to provide the historical development of STEM education in the United States, along with a summary of the literature associated with the STEM pathway, or pipeline, concept. In particular, literature that focused on the educational junctures that occur in the pipeline along with the pertinent aspects of how demographics (particularly of those underserved in STEM) and STEM outreach opportunities influence

pipeline persistence were highlighted. Finally, an exploration of the SCCT framework for understanding these variables was discussed, along with how SCCT influences the social cognitive factors of self-efficacy and STEM career intent.

The literature showed that while federal intervention has been active for more than 40 years to increase the number of students who pursue STEM, many, especially from underserved populations, continue to leave STEM pathways prior to beginning STEM careers. In particular, race and gender appear to be factors that predict whether a student will pursue a STEM career as non-white and non-male students exit the pipeline more frequently. This may be due to lack of exposure to educational opportunities in STEM at the secondary level, lack of preparation for STEM coursework, or lower interest in STEM among these groups. Additionally, socioeconomic and other external factors such as lack of familial support may impact these groups and their STEM persistence. Outreach programs may play a role in closing this gap due to their positive impact of factors such as: experiential learning with hands-on STEM activities; providing positive STEM role models; increasing academic performance in STEM subjects; relating STEM to students' relevant life experiences; and providing support for applying to STEM degree programs. In the following chapter, SCCT will be used to model these factors to begin an examination of how outreach efforts may promote student retention in STEM careers.

Chapter Three: METHODOLOGY

The purpose of this study was to identify the factors that predict students' STEM self-efficacy and STEM career intent. This chapter explicates the research design, which includes descriptions of the sample, data collection, variable selection, and statistical analyses. Drawing on SCCT (Lent et al., 1994), the research questions that guided this study cluster around two separate factors: student STEM self-efficacy and student intent to major in STEM. This led to two primary research questions with several sub-questions:

1. What are the factors that influence student STEM self-efficacy?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and STEM self-efficacy?
    b. What is the relationship between student level factors (e.g., race, gender, and age) and STEM self-efficacy?
    c. Controlling for student-level factors, what is the relationship between program-level factors (program type, length, etc.) and STEM self-efficacy?
2. What are the factors related to student intent to major in STEM fields?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and intent to major in STEM fields?
    b. What is the relationship between student-level factors (e.g., race, gender, and age) and intent to major in STEM fields?
    c. Controlling for student factors, what is the relationship between program-level factors (program type, length, etc.) and intent to major in STEM fields?

This research also attempted to determine the extent to which these factors influence and predict both STEM self-efficacy and intent to major in STEM in students. To restate these research questions as a traditional hypothesis:

Null Hypothesis: Out-of-school learning experiences, student-level factors, and program-level factors are not predictive of student STEM self-efficacy or student intent to major in STEM fields (H_0: $\chi = 0$);

Alternative Hypothesis: Out-of-school learning experiences, student-level factors, and program-level factors are predictive of student STEM self-efficacy or student intent to major in STEM fields (H_1: $\chi \neq 0$).

Data Collection

Using both descriptive and inferential statistics, relevant variables related to student self-efficacy, future academic performance, and student attitudes toward STEM careers were explored. These variables are taken from the Student Attitudes toward STEM (S-STEM) survey with data collected between 2011 and 2016. The following section will explore the construction of the survey instrument, the analysis procedure, a description of the sample, and an explanation of the study variables.

Source

As previously mentioned, the study of out-of-school STEM education programs, or STEM outreach, is a critical area of research due to the policy implications regarding the construction and usefulness of these programs as impactors of student attitudes toward STEM. This study examines a large sample of students who have participated in outreach programs, primarily at a large, southeastern U.S. public university. This purposive sample will allow for

the exploration of beliefs, attitudes and interests of students at the leading edge of informal STEM educational initiatives.

S-STEM Survey

While much of the early focus on meeting the demand for STEM professionals centered on increasing student achievement in STEM related coursework, a 2010 report from the President's Committee of Advisors on Science and Technology suggested that increasing student attitudes towards STEM could be just as impactful. That same year, a public foundation in the southeastern U.S. created a STEM initiative designed to reach across the state of North Carolina that focused on providing support for hands-on, experiential STEM opportunities for the state's rural student population. The goal of this initiative was to build a support structure for rural students interested in pursuing STEM careers. Concurrently, an urban initiative designed to take advantage of North Carolina's high concentration of STEM and STEM-related businesses was seeking to create a series of STEM-themed K-12 schools. One of the goals for both programs was the improvement of student attitudes toward STEM, particularly for students traditionally underrepresented in STEM careers and underserved by high quality STEM programming.

A research team at the aforementioned university developed an instrument designed to measure changes in student attitudes, the Student Attitudes toward STEM Survey (S-STEM). While the S-STEM is not the only instrument measuring student attitudes toward science or mathematics (cf., Enochs & Riggs, 1990; Minner et al., 2012), its ability to measure attitudes across multiple dimensions of STEM with a parallel set of items and constructs made it a useful new tool in understanding the often-interdisciplinary nature of STEM-related careers. The S-STEM instrument has been administered to more than 15,000 K-12 students with validated versions of the survey developed for students in grades 6 through 12 (middle and high school

version) and grades 4 and 5 (elementary version). Initial factor analysis of the survey yielded valid and reliable results in measures of student attitudes across several constructs and career interest items, and the survey has been found to be consistent for students of various ages, ethnicities, and genders (Unfried et al., 2015).

In the S-STEM Survey, three scales measure student attitudes toward four STEM subjects: science (9 items), mathematics (8 items), and engineering/technology (9 items). Each item is measured on a five-point Likert scale from 1 = *strongly disagree* to 5 = *strongly agree.* Students are prompted to agree or disagree with self-efficacy items, such as 'I am sure I could do advanced work in math,' and expectancy value items, such as 'I will need a good understanding of math for my future work.' Sample items can be seen in Table 3.1. The survey intentionally combines items measuring engineering and technology attitudes into one construct as engineering and technology are commonly perceived by students as being an integrated curriculum (Wells, 2016). The fourth construct measures students' attitudes toward 21st century skills. 21st century skills can be thought of as the competencies in critical thinking, communication, creativity, and collaboration necessary for future workers in STEM to be able to complete job-related tasks. While some STEM positions require advanced degree attainment and specialized training, many more require basic STEM competency along with these 21st century skills (Carnevale et al., 2011).

Table 3.1

Sample Items from the Four Attitudes Constructs[a]

Construct	Sample Items
Science	I am sure of myself when I do science. I will need science for my future work.
Mathematics	I am the type of student to do well in math. I would consider choosing a career that uses math.
Engineering and Technology	I like to imagine creating new products. I believe I can be successful in a career in engineering.
21st Century Skills	I am confident I can set my own learning goals.

[a] Table adapted from Wiebe et al. (2018).

Career Interest Section

The S-STEM Survey measures student career interest using a four-point scale (Not *So Interested* to *Very Interested*) in twelve STEM career pathways: physics, environmental work, biology and zoology, veterinary work, mathematics, medicine, earth science, computer science, medical science, chemistry, energy, and engineering. These pathways were developed from a robust list of STEM careers found in the *Occupational Outlook Handbook* (U.S. Bureau of Labor Statistics, 2011). The 43 pilot careers were then refined using exploratory factor analysis. Each item defines a career pathway and gives a list of related occupations spanning several years' worth of educational and vocational training. An example career item reads, *"Physics: is the study of basic laws governing the motion, energy, structure, and interactions of things and*

matter. This can include studying the nature of the universe. (aviation engineer, alternative energy technician, lab technician, physicist, astronomer).”

Academic or External Items

The survey also asked students how well they expect to perform in their upcoming English, mathematics, and science coursework (*Not Very Well, OK/Pretty Well,* or *Very Well*). This question served as a substitute for student academic performance since student academic achievement is not captured by the survey. While performance in English class may not initially seem to be congruent with the rest of the survey, previous research has shown the importance of literacy in STEM understanding (Deng et al., 2019). Additionally, students are asked if they know any STEM professionals. Each of these questions was designed to account for external factors that may influence student interest in STEM.

Sample

The S-STEM Instrument was given to 8,177 4th through 12th grade students from North Carolina public schools that were participating in STEM-focused education outreach initiatives. Of the 8,177 respondents, 7,862 were in 118 schools across multiple school districts, while the remaining students were either homeschooled or had undetermined school status. Of the 7,862 respondents, 3,544 students were participants in 17 programs implementing STEM outreach at North Carolina State University. The remaining students in the sample were participants in programs not housed or managed by the University, respectively. The students completed the S-STEM survey online between 2011 and 2017. The survey was administered anonymously, with only grade and school information collected. Typical pre-program survey administration occurred on the first day of programming for one week or longer interventions; for shorter programs, survey administration was scheduled to occur before any programmatic elements were

delivered. In each case, the goal was to capture student attitudes and interests before receiving any input from the program in which they were participating. Correspondingly, post-program survey administration occurred either 1) after the conclusion of a program; or 2) as close to the end of programming feasibly possible (e.g., the beginning of the last day of programming or between programmatic sessions near the end of the day). An approximate response rate of 79.1% was the level of completion of both pre- and post-intervention surveys.

Approximately 1% of the surveys had no variation in responses across all items, indicating student disinterest, and were removed from the dataset. Of the remaining survey responses after cleaning, 89.9% of responses had no missing data. Missing data percentages for each survey item ranged from 0.0% to 7.9%, with a mean of 4.67% and standard deviation of 2.1%. The data was examined for normality and was revealed to be skewed to the positive end of the scale. An examination of the residuals of the dataset revealed that these did approximate a normal distribution, as seen in Figure 3.1, therefore the data could be used without transformation (Weaver, 2017).

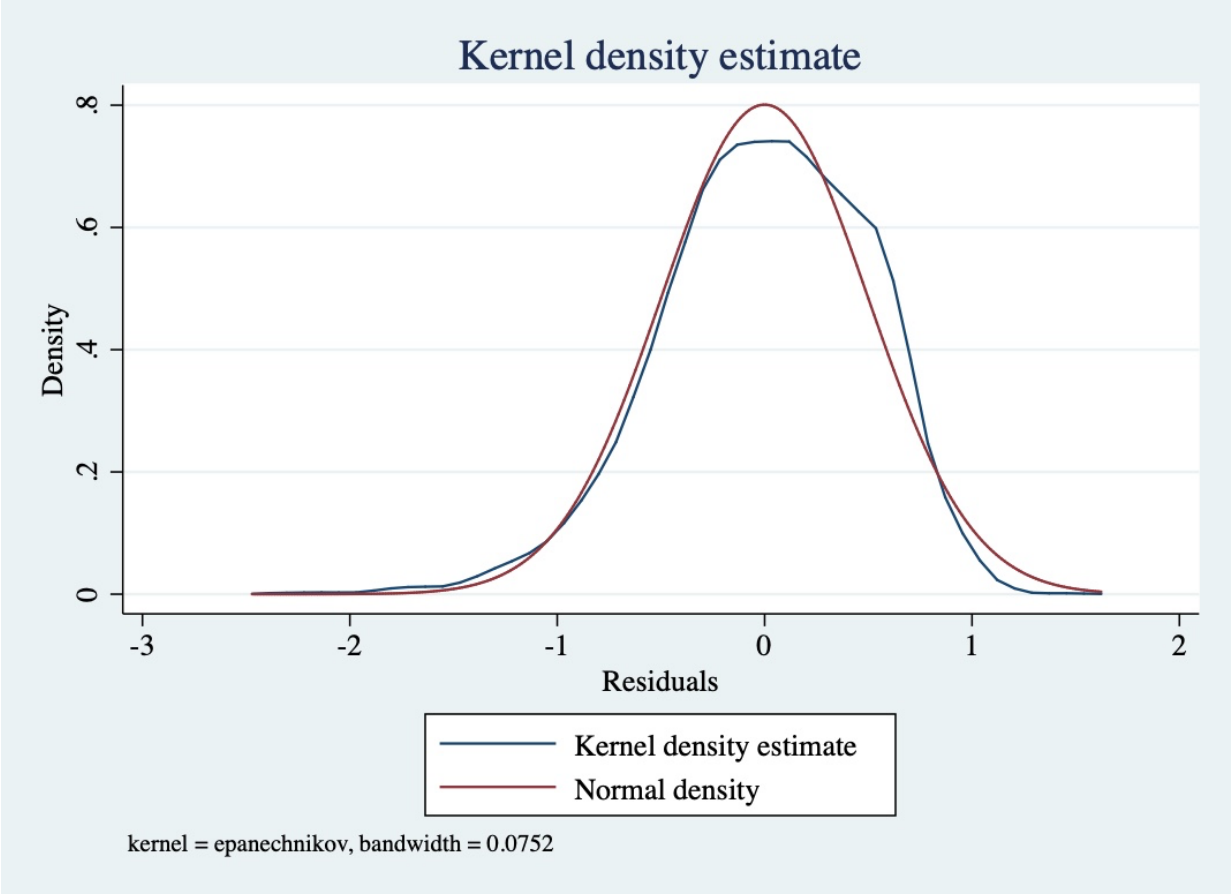

Figure 3.1 Kernel Density of S-STEM data mapped over a normal distribution curve

Survey respondents were 1) 58.3% male and 41.7% female, and 2) 53.7% Caucasian, 25.4% African American, 3.8% Latin@ (captured as Hispanic/Latino on the instrument), 5.0% Multiracial, 2.0% Other, and 8.4% Asian/Pacific Islander. This demographic distribution deviates from the distribution of North Carolina students (64.0% Caucasian, 21.5% African American, 8.9% Hispanic/Latino; Census Bureau, 2016) and U.S. national distributions (62.0% Caucasian, 12.6% African American, 17.3% Hispanic/Latino; Musu-Gillette et al., 2016); this is not unexpected for a self-selected sample of STEM outreach participants as the recruitment of underrepresented students is often a mission of these programs (Myers & Pavel, 2011).

Variables

The variables chosen for this study were selected based on their alignment with Lent, Brown and Hackett's (1994) SCCT framework and the empirical literature on the factors that influence science self-efficacy and STEM career intent in adolescents. Table 2 specifies the variables used from the dataset (note, as explained in later sections, some of the variables have been re-coded, transformed and re-classified). Descriptions of the variables, their meaning, and how they were coded for this study follows.

Table 3.2

Variables from S-STEM Survey Used in Analysis

Variable	Description
Student Level	
X1GRPRACE	Student race is overrepresented/underrepresented in STEM fields
X1GRADE	Respondent Grade Level
X1Black	Respondent is Black
X1Asian	Respondent is Asian
X1Hispanic	Respondent is Hispanic/Latino/Latina
X1AmericanInd.	Respondent is American Indian or Native Alaskan
X1Pac.Islander	Respondent is Hawaiian or Pacific Islander
X1Gender	Respondent gender
XISCIID	Scale of science self-efficacy
XISMIID	Scale of math self-efficacy
XISEIID	Scale of engineering/technology self-efficacy
XI21STIID	Scale of 21st century self-efficacy
XISCOE	Scale of science future performance
XISMOE	Scale of math future performance
XIENGOE	Scale of English future performance
X1DOSAGE	Times Participated in S-STEM documented outreach

Table 3.2 continued

X1PREPOST	Measure evaluated before or after program intervention
S1SCAREER1	STEM Career Interest-Physics
S1SCAREER2	STEM Career Interest-Environment
S1SCAREER3	STEM Career Interest-Mathematics
S1SCAREER4	STEM Career Interest-Earth Science
S1SCAREER5	STEM Career Interest-Computer Science
S1SCAREER6	STEM Career Interest-Chemistry
S1SCAREER7	STEM Career Interest-Energy
S1SCAREER8	STEM Career Interest-Engineering
S1SCAREER9	STEM Career Interest-Biology & Zoology
S1SCAREER10	STEM Career Interest-Veterinary Science
S1SCAREER11	STEM Career Interest-Medicine
S1SCAREER12	STEM Career Interest-Medical Science
P1SCISTEMPRO	Respondent knowledge of STEM professional
P1SCICOLLEGE	Respondent STEM major intent
Program Level	
X1CONTROL	Program
X1CONTROL2	School type
X1LOCALE	Rural/Urban Program locale
X1TITLEI	Recognized at Title I School

Outcome Variables

Science, Math, Engineering/Technology, and 21st Century Self-Efficacy. A mean construct score was calculated for each student on each of the four attitudes factors (XISCIID, XISMIID, XISEIID, XI21STIID). These scores range from 1 to 5 using the Likert model. The coefficient of reliability for the scale was determined from item reliability analysis of the items comprising each respective scale. Cronbach's alpha was determined to be 0.92. These variables were then combined to form a single construct score representing a student's overall STEM Self-Efficacy.

Student Intent to Major in STEM. P1SCICOLLEGE is the variable that measured student STEM intent to major in STEM fields (Ingels et al., 2011). The survey question asked, "Please list an area (or college major) you are interested in studying in college." This response was coded binary as STEM/non-STEM. The STEM/non-STEM categories were developed from the list defined by earlier research from the US Bureau of Labor Statistics.

Predictor Variables (Student level data)

Student Outreach Dosage. STEM program dosage (S1SDOSAGE), was tabulated from a self-reported internal measure. Dosage is defined as the number of times a participant has engaged in a STEM outreach program as measured by their participation in the S-STEM survey. In this study context, 'high' dosage students are those with eight or more outreach participation opportunities, 'medium' represents 7 to 5 outreach experiences, and 'low' dosage participants had four or fewer STEM outreach interventions. No participant had more than 11 participation opportunities, while each student had at least one. The demarcation between the dosages levels was determined after a visual inspection of the dosage data as will be presented in Chapter 4.

Person Inputs. Consistent with the SCCT theoretical model of student career choice, several person input variables were included in this study. Level-l data assesses student demographic characteristics such as race (X1Black, X1Asian, X1Hispanic, X1American Ind., X1Pac. Islander) and sex (X1Gender), as well as measures such as science attitudes (X1SCIID). Additionally, whether or not the respondent was completing the instrument before or after participation in an out-of-school, or informal, STEM experience (X1PREPOST) and student grade level at the time of participation (X1GRADE) were also captured.

Race/ethnicity. The variables that denote a student's race and ethnicity were included in the model and include X1Black, X1Hispanic, X1Asian, X1American Indian, and X1Hawaaian/Pacific Islander. X1White was left out of the model because it serves as the reference group. Individual race/ethnicity categories were recoded using dummy variables to indicate a specific race (1= yes and 0 = no). Race/ethnicity was then further redefined as a dichotomous variable representing overrepresented and underrepresented students. Based on current demographic analyses (National Center for Science and Engineering Statistics, 2019), White and Asian students were categorized as overrepresented in STEM, and all other races/ethnicities were categorized as underrepresented in STEM.

Gender. The variable X1SEX characterizes the student's gender (male = 1, female = 2). The gender of the sample member was captured from self-reported data. For the purposes of this study, any regression results have 'male' as the reference group.

STEM Attitudes. Before constructing a STEM Self-Efficacy score, respondents' individual measures of Science, Engineering/Technology, Mathematics, and 21st Century Skill Self-Efficacy were measured with the S-STEM Survey. As mentioned above, these scores range from 1 to 5 on a Likert scale, with 1 representing 'Strongly Disagree' and 5

representing ‘Strongly Agree.’ Several of the items on both the Science and Mathematics subscales were negatively worded to strengthen initial measures of validity for the survey instrument. For the purposes of analysis these items were reverse coded.

Future performance. A composite variable was created to represent outcome expectations based on the SCCT model (Lent et al., 1994). The SCCT model defines outcome expectations as the motivation to either participate or not participate in specific activities based on expected outcomes. In essence, students participate in more rigorous science-related activities based on their expectations of what will happen as a result of participating. The original order of the Likert scale (5 = strongly agree, 4 = agree, 3 = neither agree or disagree, 2 = disagree, 1 = strongly disagree) was kept and results are interpreted as the higher the score, the more positive the student view on future performance (i.e., the student disagrees that participating in science/math activities will negatively impact them).

Predictor Variables (School Level Data)

Contextual influences proximal to career choice. Additional variables at level 2 of the MLM analysis (i.e., the program level) were included in this study and identified as Contextual Influences Proximal to Choice Behavior based on the SCCT model (Lent et al., 1994). These variables are consistent with characteristics of the student’s context during the high school years and when students start to make career choices. These program-level variables were included in the MLM analysis to determine how students in different program environments (type and locale) and involvement in programs with different background characteristics (e.g., Title I school attendees) might relate to students’ STEM self-efficacy and STEM career intent. School resources have been shown to be a significant factor in whether or

not students receive a quality education, especially as it relates to science and math (Russell & Atwater, 2005).

Title I Status. The dichotomous variable X1TITLEI represents whether the school of the student has been governmentally designated as a Title I school. Title I schools are defined as those with high numbers of students from low-income families (Department of Education, 2018)

Program and School type. The variable X1CONTROL represents the STEM outreach program attended by the respondent. The variable X1CONTROL2 represents the student's school classification as public, private or other (such as homeschooled). This variable was originally coded as 1 = public, 2 = private, and 3 = other. The variable was re-coded using dummy variables (0 = yes, 1 = no) to represent each of the three codes. Public schools were used as the reference group in the MLM analyses.

Locale. The variable X1LOCALE represents the metropolitan area that the program resides in and provides insight into the location, environment and population that surrounds the school. Program locale was originally coded as 1 = city, 2 = suburban, 3 = town, and 4 = rural. The variable was recoded and grouped using dummy variables (0 = both city and suburban, 1 = town and rural) to represent each of the four codes. Urban was used as the reference group in the MLM analyses.

Multilevel Modeling

Multilevel Modeling (MLM) is particularly useful in educational research when analyzing data that naturally has a hierarchical structure of interrelated variables where individuals are the main unit of interest at lower levels, but are "nested" within contextual structures, such as programs or schools, that are the main unit of analysis at higher levels

(Tabachnick & Fidell, 2007; Raudenbush & Bryk, 2002). Prior research has shown that practices within schools are linked to measures such as motivation and career aspiration, variables linked to major intent (Mann et al., 2015). For this dataset, since students are nested in programs, using OLS (ordinary least squares) regression would violate the criterion of independent observations since the program level likely has an effect on students (Figure 3.2). Previous research using mixed effects analysis on data measured by the S-STEM instrument has shown this approach can yield promising results, however this work did not consider the variance between programs (Saw et al., 2019).

Clustering of observations within groups or hierarchies leads to correlated error and biased estimates of parameter standard errors when not accounted for (Raudenbush & Bryk, 2002). Additionally, variance parameters that provide insight into model fit can be biased if standard multiple regression is employed for nested data (Snijders & Bosker, 2011). The mixed effects model considers the repeated measures of the respondents with the random effects term at level 1 of the model.

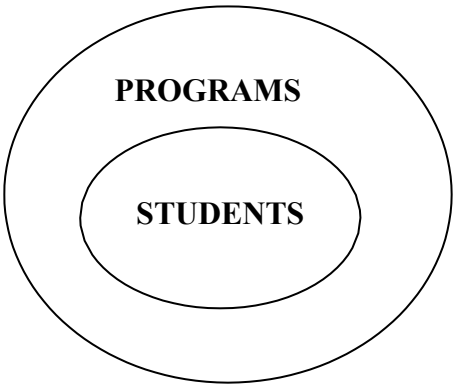

Figure 3.2 Diagram of sample clustering

This study employed a null, or "unconditional," model containing no independent variables to predict the level 1 (student characteristics–race, sex, dosage, contextual variables) intercept of science self-efficacy and STEM career intent as a random effect of students. The

unconditional model was then used as the base to construct the models that followed, beginning with the added level 1 (student characteristics–race, sex, grade level, etc.) variables, the addition of the career interest variables, future performance variables, and knowledge of STEM professionals variables, and then finally the level 2 (program-specific) variables.

Model Specification

To account for the variance associated with student STEM self-efficacy, this study used a mixed effects generalized linear model (MEGLM). MEGLM is designed to allow for constraints in the model, such that for a linear model the effect size of specific variables can be determined. The dependent variables STEM self-efficacy and STEM major intent were contained in the first level of the model. The intercepts in the first order model were derived from the slopes and error term from the level 2 model.

The equations below illustrate the fully specified MEGLM model for predicting STEM self- efficacy and the logistic model for predicting STEM major intent that was used to assess the impact of student-level effects (student characteristics–race, sex, SES, contextual variables) and program-level (school type, program).

STEM Self-Efficacy Fully Unconditional Model (Null)

$STEMEFFij = \gamma 00 + u0j + rij$

Where: $\beta_{0j} = \gamma_{00} + u_{0j}$,

$STEMEFF_{ij}$ = confidence for student i and program j, β_{0j} = mean confidence rating for student i
γ_{00} = grand mean for all STEM self-efficacy
u_{0j} = random effect associated with Program j (level 2 effect)

r_{ij} = random effect associated with student i in Program j (level 1 effect)

STEM Self-Efficacy Random Effects Model

$STEMEFF_{i}ij = \gamma 00$

$+ \gamma 10 * X1underrepresentedij$
$+ \gamma 20 * X1sexij$
$+ \gamma 30 * grade$
$+ \gamma 40 * X1prepostj$
$+ \gamma 50 *$X1$dosageij$
$+ \gamma 60 *$21stcenturyij
$+ \gamma 70 * sciencefutureperformanceij$
$+ \gamma 80 * mathfutureperformanceij$
$+ \gamma 90 * Englishfutureperformanceij$
$+ \gamma 100 *$*knowledge of STEM Professional – yesij*
$+ \gamma 110 *$*STEM career intent_ij*
$+ u0j + rij$

Where: $\beta 0j = \gamma 00 + u0j$, $\beta 1j = \gamma 10 + u1j$, $\beta 2j = \gamma 20 + u2j$, $\beta 3j = \gamma 30 + u3j$

β_{1j}- β_{3j} = regression coefficients indicating how STEM self-efficacy is distributed in (Program) j

as a function of the measured student characteristic;

γ_{00} = average intercept across the level 2 units;

$\gamma_{10\text{-}30}$ = average regression slope across the level 2 units;

u_{0j} = unique increment to the intercept associated with (Program) j;

and $u_{1j\text{-}3j}$ = unique increment to the slope associated with (Program) j.

STEM Self-Efficacy Random Effects with Interaction

$STEMEFFij = \gamma 00$
$+ \gamma 10 * X1underrepresentedij$
$+ \gamma 20 * X1sexij$
$+ \gamma 30 * grade$
$+ \gamma 40 * X1prepostj$
$+ \gamma 50 *$X1$dosageij$
$+ \gamma 60 *$21stcenturyij
$+ \gamma 70 * sciencefutureperformanceij$
$+ \gamma 80 * mathfutureperformanceij$
$+ \gamma 90 * Englishfutureperformanceij$
$+ \gamma 100 *$*knowledge of STEM Professional – yesij*
$+ \gamma 110 *$*STEM career intent_ij*
$+ u0j + rij$

STEM Self-Efficacy Intercepts-As-Outcomes Model

$STEMEFFij = \gamma 00 + \gamma 01 * X1CONTROL1j + \gamma 02 * CONTROL2j + \gamma 03 * X1TITLEIj$

STEMEFFij = γ00
+ γ10 X1underrepresentedij*
*+ γ20*X1sexij*
*+ γ30*grade*
*+ γ40*X1prepostj*
*+ γ50**X1*dosageij*
*+ γ60**21stcentury*ij*
*+ γ70*sciencefutureperformanceij*
*+ γ80*mathfutureperformanceij*
*+ γ90*Englishfutureperformanceij*
*+ γ100*knowledge of STEM Professional – yesij*
*+ γ110*STEM career intent_ij*
+ γ120 X1LOCALEj*
*+ γ130*school typej*
*+ γ140*program typej*
+ γ150 Title I Status – X1TITLEIj*
+ u0j+ rij

Where: $\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Program type})_j + \gamma_{02}(\text{ School Type})_j + \gamma_{03}(\text{Title I})_j + \gamma_{04}(\text{locale})_j + u_{0j}$;

$\beta 1j = \gamma 10 + u1j$;

γ_{00}: average intercept across the level-2 units $\gamma_{01} – \gamma_{09}$: average slope across level 2 units;

$\gamma_{10\text{-}30}$: average regression slope across the level 2 units;

and u_{0j}: unique increment to the intercept associated with (Program) j $u_{1j\text{-}3j}$: unique increment to the slope associated with (Program) j.

STEM Major Intent Fully Unconditional Model (Null)

$\text{Prob}(\text{P1SCICOLLEGE}_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta ij = \beta 0j$ $\text{P1SCICOLLEGE2}_{ij} = \beta_{0j} + r_{ij}$ Where: $\beta_{0j} = \gamma_{00} + u_{0j}$,

$\text{P1SCICOLLEGE2}_{ij}$ = STEM career intent for student i and Program j, β_{0j} = mean career intent rating for student i:

γ_{00} = grand mean for all STEM career intent constructs;

u_{0j} = random effect associated with school j (level 2 effect)

r_{ij} = random effect associated with student i in school j (level 1 effect)

STEM Major Intent – Random Effects Model

Prob(P1SCICOLLEGE $_{ij}$=1|β_j) = ϕ_{ij}

log[ϕ_{ij}/(1 - ϕ_{ij})] = η_{ij}

ηij = *β0j + β1j*(* X1STEM Underrepresentedij) + β2j*(X1science self-efficacyij) + β3j*(X1math self-efficacyij) + β4j*(X1engineering self-efficacyij) + β5j*(X1sexij) + β6j*(X121st century self-efficacyij) + β7j*(science future perfomanceij) + β8j*(math future perfomanceij) + β9j*(English future perfomanceij)+ β10j*(STEM career interestij) + β11j*(STEM professional knowledgeij) + β12j*(dosage_ij) + β13j*(grade level_ij) + β14j*(prepost status_ij).*

Where: β0j = γ00 + u0j, β1j = γ10 + u1j, β2j = γ20 + u2j, β3j = γ30 + u3j;

β_{1j}- β_{3j} = regression coefficients indicating how STEM career intent is distributed by (Program) j as a function of the measured student characteristic;

γ_{00} = average intercept across the level 2 units;

$\gamma_{10\text{-}30}$ = average regression slope across the level 2 units;

u_{0j} = unique increment to the intercept associated with (Program) j $u_{1j\text{-}3j}$ = unique increment to the slope associated with (Program) j

STEM Major Intent Intercepts as Outcomes Model

Where: β_{0j} = γ_{00} + γ_{01}(Program type)$_j$ + γ_{02}(School Type)$_j$ + γ_{03}(Title I)$_j$ + γ_{04}(locale)$_j$ + u_{0j};

ηij = β_{0j} +

+ γ10 X1underrepresentedij*
*+ γ20*X1sexij*
*+ γ30*grade*
*+ γ40*X1prepostj*
*+ γ50*X1dosageij*
*+ γ60*scienceself-efficacyij*
*+ γ70*mathself-efficacyij*
*+ γ80*engineeringself-efficacyij*

$+ \gamma 90 * 21\text{stcentury}_{ij}$
$+ \gamma 100 * sciencefutureperformance_{ij}$
$+ \gamma 110 * mathfutureperformance_{ij}$
$+ \gamma 120 * Englishfutureperformance_{ij}$
$+ \gamma 130 * knowledge\ of\ STEM\ Professional - yes_{ij}$
$+ \gamma 140 * STEM\ career\ intent\_ij$
$+ \gamma 150 *\ X1LOCALE_j$
$+ \gamma 160 * school\ type_j$
$+ \gamma 170 * program\ type_j$
$+ \gamma 180 *\ Title\ I\ Status - X1TITLEI_j$
$+ u0j$

Chapter Summary

Chapter III described the methodology, data collection, sample, instrument, variables, and the specific statistical processes that were used to address the research questions. Sampling procedures for the programs and students were also discussed in addition to response rates for the participants and the surveys that were administered. A discussion of how each variable was operationalized was also offered in relation to the development of a mixed effects model to predict STEM self-efficacy and intent to pursue a STEM major. Finally, a discussion of the statistical analyses and models was presented.

Chapter Four: RESULTS

The purpose of this study is to identify the factors that predict students' STEM self-efficacy and STEM career intent. The results from this work can be used to inform both capacity building for STEM outreach efforts and both local and national STEM education policy. Chapter IV begins with a review of the purpose of the study and is followed by a description of the research sample and research questions guiding the study. Descriptive statistics for the sample will also be presented along with preliminary statistical analyses (e.g., correlation matrices), followed by the results of the mixed-effects linear model. The mixed effects model will be used to address each research question; for Research Question One and its sub-questions (RQ 1a-c) the generalized linear model will be fitted to the STEM Self-Efficacy variable. The random effects of the program variable on STEM Self-Efficacy (RQ 1a) will be measured, followed by the fixed effects of demographic variables and other student level factors (RQ 1b). Next, the random, unobservable effects of the program level, for example the type of school a student attends or the geographic area of the program they attended, will be investigated (RQ 1c). These same variables will also be examined for their potential effect on the binary outcome variable measuring a student's intent to major in a STEM field (RQ 2a-c) using a logistical fit of the mixed-effects model.

Using the Student Attitudes toward STEM (S-STEM) Survey, a survey of student attitudes about STEM self-efficacy, future academic performance, and career interests, self-reported information was gathered from a sample of more than 7,000 students from at least 118 different schools to determine which factors predict STEM self-efficacy and STEM career intent.

Research Questions

1. What are the factors that influence student STEM self-efficacy?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and STEM self-efficacy?
    b. What is the relationship between student level factors (e.g., race, gender, and age) and STEM self-efficacy?
    c. Controlling for student-level factors, what is the relationship between program-level factors (program type, length, etc.) and STEM self-efficacy?
2. What are the factors that influence student intent to major in STEM fields?
    a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and intent to major in STEM fields?
    b. What is the relationship between student-level factors (e.g., race, gender, and age) and intent to major in STEM fields?
    c. Controlling for student factors, what is the relationship between program-level factors (program type, length, etc.) and intent to major in STEM fields?

Descriptive Statistics

Data collected both directly from the S-STEM survey instrument and from secondary analysis of certain S-STEM variables were used as predictors in the mixed effects models of STEM self-efficacy and student major intent. Of the 8,177 students who were administered the S-STEM instrument, 315 (3.85%) had missing responses for at least one variable captured in the survey, leaving 7,862 respondents. This value includes each instance of student response to the

S-STEM survey; descriptive statistics for unique instances of the instrument are presented in Appendix A.

To clean the data for analysis, these students were removed using the procedure for listwise deletion, leaving only complete responses. Using the technique described in Wiebe et al. (2018) the data was initially cleaned to both remove non-responses and generalize the structure of the remaining responses. This was particularly true for responses where students were required to type their own text; for example, one student might enter "Civil Engineering" as a potential major, while another answered, "Civil Engineer." While these responses were not strictly identical, for the purposes of analysis they were coded the same. The majority of S-STEM respondents came from North Carolina based public schools' systems, with more than 31% of the respondents (n=2,438) residing in the same county (Wake) as the university itself. The only school system outside of the state of North Carolina that provided more than 1% of responses was the Blair County School System in Pennsylvania (n=138). The school districts with the largest share of respondents are provided in Table 4.1. Student variables were input at the first level of the predictive model and contribute to our understanding of the variance within programs, which reflect the differences among the individual students. The following section describes Level 1 variable characteristics.

Descriptive statistics are presented in Tables 4.2 through 4.7. Results for the respondent sample are provided, including frequency, means and standard deviation, the maximum and minimum values for scale scores, and the mean and standard deviations (continuous only) for each variable.

Table 4.1

Distribution of S-STEM Respondents from Counties or Districts with More Than 100 Participants

School District	Frequency	Percent
Wake County Schools	2,438	31.00
Chapel Hill-Carrboro City Schools	243	3.10
Nash-Rocky Mount Schools	243	3.10
Charlotte-Mecklenburg Schools	198	2.52
Durham Public Schools	195	2.48
Guilford County Schools	121	1.54
Johnston County Schools	114	1.45
Pitt County Schools	111	1.41

Note. N=7,682 for descriptive statistics unless otherwise noted.

Table 4.2

Distribution of S-STEM Respondents by Grade Level

Grade Level	Frequency	Percent
3	3	0.04
4	10	0.13
5	51	0.65
6	939	11.94
7	1,269	16.14
8	1.221	15.53
9	825	10.49
10	831	10.57
11	1,230	15.64
12	1,448	18.42

Table 4.2 continued

13[a]	36	0.46

[a] 13 represents students that selected the survey option 'Completed High School.'

Student grade level is a self-reported item in this study and is noted in Table 4-2. As mentioned in Chapter III, the two versions of the S-STEM Survey are validated for grade 4-5 and grades 6-12, respectively. Importantly, both versions of the instrument measure the same construct and thus, we have proceeded with merging the data sets at the construct response level. The sample does not model the typical distribution of K-12 students in North Carolina; the percentage of 5th through 8th grade students is larger than average. The majority of respondents were high school students in grades 9-12; this is typical of STEM outreach efforts that are more likely to engage with older students. The grade '13' is representative of respondents who are pre-college students but who note that they have completed their requirements for high school graduation.

Table 4.3

Distribution of S-STEM Respondents by Gender

Gender	Frequency	Percent
Male	4,576	58.2
Female	3,286	41.8

Student gender was coded 1 for male and 2 for female. The mean was 1.42, with a standard deviation of 0.493, which indicates a distribution with a larger percentage of males (58.2%) compared to females (41.8%) in this study. Current techniques for inclusive survey design would suggest that defining gender strictly in these terms is problematic. However, the goal of this S-STEM Survey question was to capture student *biological sex,* not gender. While

the wording of this item is incorrect, due to its use in the survey, for analysis purposes this study will maintain use of the term 'Gender.'

Table 4.4

Distribution of S-STEM Respondents by Race/Ethnicity

Race/Ethnicity	Frequency	Percent
American Indian	192	2.44
Asian	659	8.38
Black/African American	1,922	24.45
Pacific Islander	24	0.31
White	4,224	53.73
Hispanic/Latino	288	3.66
Multiracial	391	4.97
Other	162	2.05

Race/Ethnicity

White. Students that self-identified as White were coded the default value. This variable had a mean of 0.537, which indicates the weighted sample population is 53.7%.

Black or African American. Students that self-identified as Black or African American were coded as an alternate value with a mean of 0.244, which indicates the weighted sample population is 24.4% African Americans are overrepresented in this sample.

Hispanic. Students that self-identified as Hispanic, Latino, or Latina were coded as an alternate value with a mean of 0.037, which indicates the weighted sample population is 3.7%.

Asian. Students that self-identified as Asian were coded as an alternate value with a mean of 0.084, which indicates the weighted sample population is 8.4%.

Pacific Islander. Students that self-identified as Pacific Islander were coded as an alternate value with a mean of 0.003, which indicates the weighted sample population is 0.3%.

Multiracial or Other. Students that self-identified as Multiracial were coded as an alternate value with a mean of 0.050, which indicates the weighted sample population is 5%. Students that either responded 'Other' or who did not provide an answer for racial identity were coded together and had a mean of 0.020, which indicates the weighted sample population is 2%.

Table 4.5

Distribution of Race/Ethnicity for S-STEM Respondents by Overrepresented/Underrepresented in STEM Labels

Race Category in STEM	Frequency	Percent
Overrepresented	4,884	62.12
Underrepresented	2,978	37.88

To capture aspects of race and ethnicity that may be difficult to discern using more granular categories, Race was recoded as a dichotomous variable with the labels of *Overrepresented* and *Underrepresented* respective to each racial group's current representation in the STEM workforce. Students who self-identified as White and Asian/Pacific Islander were coded as Overrepresented and while the remaining racial groups were categorized as Underrepresented (Beede, Julian, Khan et al., 2011; Funk & Parker, 2018). In the sample, 62.12% of respondents were members of groups overrepresented in the STEM workforce, while 37.88% were members of underrepresented racial groups.

Table 4.6

Descriptive Statistics for Dosage Level

	n	*M*	*SD*	Min	Max
Dosage	7,682	2.39	1.59	0	11

Table 4.7

Distribution of S-STEM Respondents by Dosage Level

Dosage Level	Frequency	Percent
Low	7,076	90.00
Medium	714	9.09
High	72	0.91

Dosage

Dosage is a measure of the number of times students participated in STEM outreach initiatives as measured by self-reporting and their participation in the outreach experiences used for this study. The majority of respondents reported participating in at least one STEM outreach effort. The mean dosage level was measured at 2.39 with values ranging from 0 to 11, with a standard deviation of 1.59. A visual examination of dosage, as presented in Figure 4.1, reveals an inflection point in the levels of STEM Self-Efficacy that occurs at the dosage measures 5 and again at 8. Prior research has used visual analysis of data to recognize when cognitive changes occur after interventions and typically notes changes such as inflective or asymptotic behavior as seen in the figure (Lane & Gast, 2014). Using these visual cues, and to create categorical variables for analysis, dosage was grouped in three levels, low (0-4 STEM experiences), medium (5-7), and high (8 or more STEM experiences).

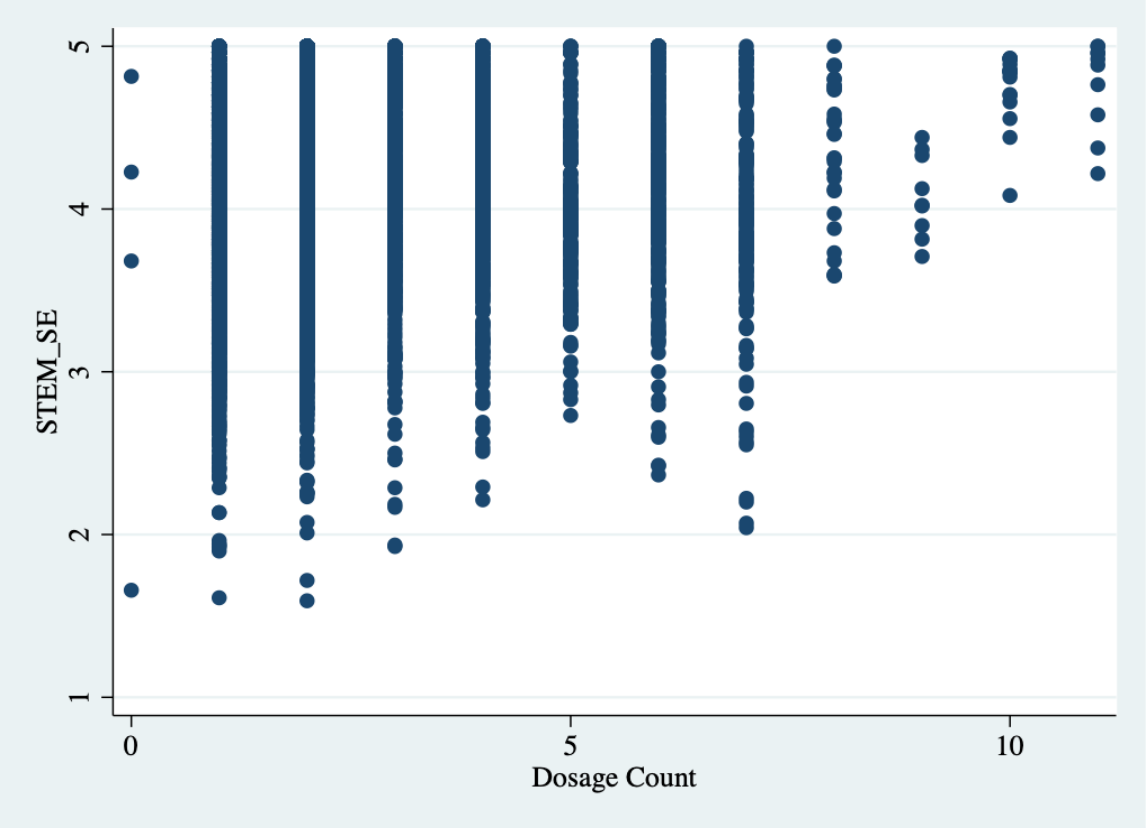

Figure 4.1 Measure of the STEM Self-Efficacy Composite Score by Dosage Level

S-STEM Construct Scores

Table 4.8

S-STEM Construct Scale Scores and Self-Efficacy Composite Score

	M	*SD*	Min	Max	Scale Items
Math Attitudes	4.16	0.74	1	5	8
Science Attitudes	4.16	0.68	1	5	9
Engineering/Technology Attitudes	4.03	0.72	1	5	9
21st Century Skills Attitudes	4.30	0.52	1	5	11
STEM Self-Efficacy Composite Score	4.12	0.55	1.59	5	

The Math, Science, Engineering & Technology, and 21st Century Skill Scale scores were measured from student responses to the S-STEM survey instrument. A series of responses asked students to evaluate their own self-efficacy from *'strongly disagree'* to *'strongly agree'* and were assigned a whole number value of 1 to 5 respectively on a Likert scale. The composite attitude scores for each construct were derived from the average scale responses of each participant on the items making up the scale containing both self-efficacy and outcome expectancy construct items. The scores for each individual item were averaged to arrive at the value for each composite score. The Science scale contained one negatively worded item that was reverse coded for analysis; the Math scale contained two such items, with the same transform applied.

The construct scores for each scale ranged from 1 to 5. The eight-item Math scale and the nine-item Science scale had similar mean construct scores (M=4.16, SD=0.74, M=4.16, SD=0.68, respectively). The mean construct score for the nine-item Engineering & Technology scale was slightly lower (M=4.03, SD=0.72), while the mean construct score for the 11-item 21st Century Skills scale was the highest overall (M=4.30, SD=0.52). Histograms of the S-STEM construct scale scores are provided in Figure 4.2. The S-STEM scales measure individual self-efficacy and outcome expectancy constructs for math, science, engineering and technology, and 21st century skills. It is worth noting that in this study these constructs were each measured individually in contrast to the fact that STEM is generally regarded as an umbrella area for policy and curricula related to the natural and formal sciences. To create a construct that assesses *STEM* Self-Efficacy, the means of the existing self-efficacy construct scale scores for science, math, and engineering and technology were used to create a STEM Self- Efficacy Composite Score (Hair, et al., 2019).

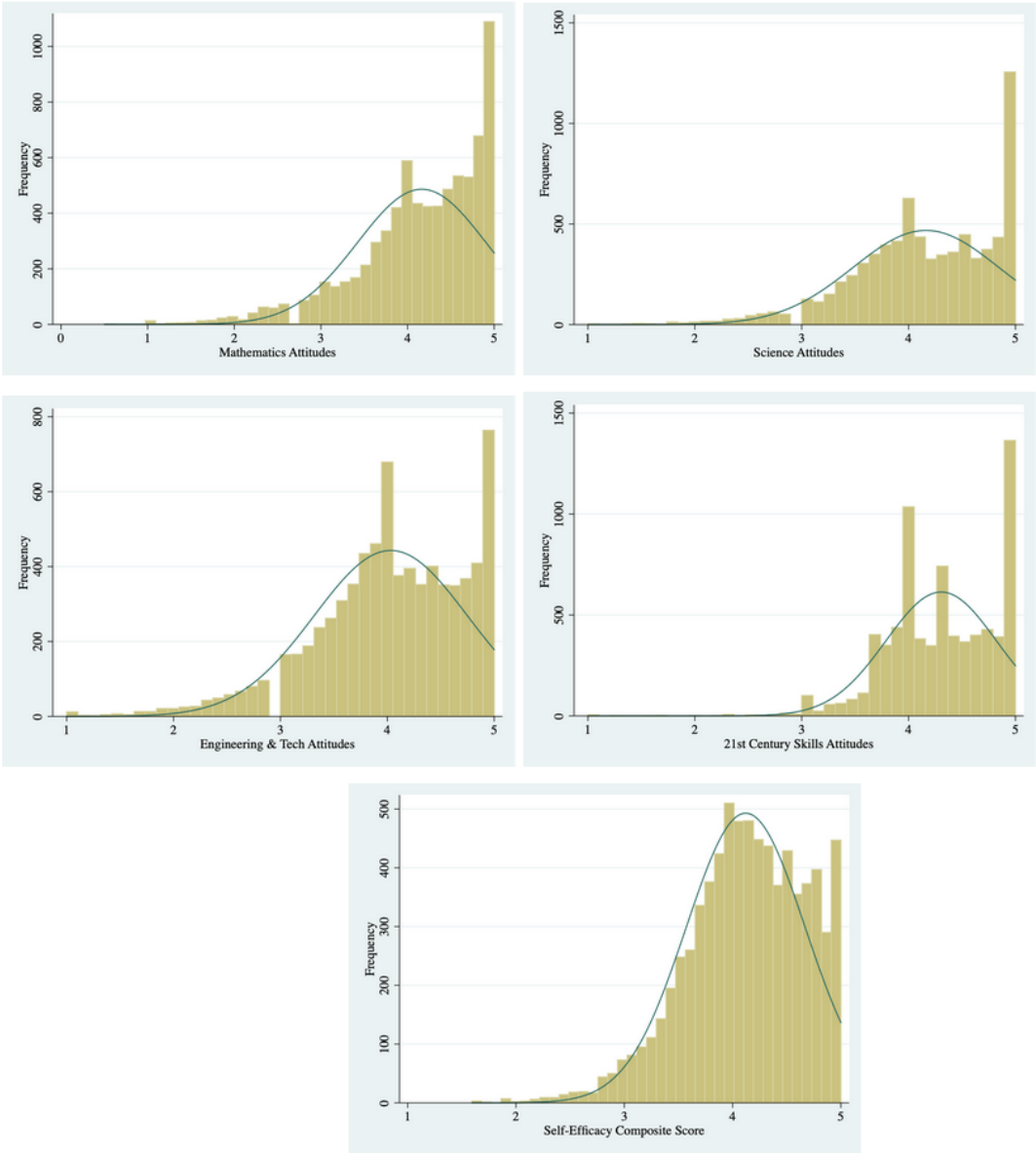

Figure 4.2 Histograms of S-STEM Attitudes Constructs and S-STEM Composite Score mapped over normal distribution curve

STEM Self-Efficacy Composite scores ranged from 1.59 to 5, with a mean of 4.12; a histogram of the STEM Self-Efficacy scores is also provided in Figure 4.2. While 21st century skills construct scores were measured using a similar scale as the self-efficacy constructs, as it is not a part of the academic disciplines related to STEM it was not included in the creation of the STEM Self-Efficacy Composite Score.

Future Performance and Advanced Coursework

The outcome expectations questions on the S-STEM instrument gauge student feelings related to academic performance on future coursework. Students could choose between *'Not Very Well,' 'Ok/Pretty Well,'* and *'Very Well,'* which were assigned a value of 1 to 3 respectively. The Advanced Coursework questions, presented here but not used in the final data analysis, ask students to express whether they plan to pursue more challenging courses in mathematics, science, or engineering and technology. Students could select *'Yes,' 'No,'* or *'Not Sure.'* Since the Advanced Coursework values were not used in the analysis, they were not recoded as binary or ordinal values. The mean and standard deviation of students' responses are presented in Table 4.9.

Table 4.9

S-STEM Future Performance and Advanced Coursework Scores

	M	*SD*	Min	Max
Future Performance - English	2.62	0.51	1	3
Future Performance - Math	2.71	0.50	1	3
Future Performance - Science	2.79	0.43	1	3
Advanced Coursework - Math	1.55	1.08	1	3
Advanced Coursework - Science	1.58	1.13	1	3
Advanced Coursework - Engineering	1.04	0.25	1	3

The STEM Career Interest section is designed to measure student interest in potential STEM fields as determined by previously developed groupings based on occupational categories from the Bureau of Labor Statistics Occupational Handbook. Each of the 12 career interest

categories asked students to evaluate their interest from '*not at all interested*' to '*very interested*' and were assigned a whole number value of 1 to 4 respectively. Engineering careers had the highest scale score among the careers (*M*=3.26, *SD*=.92), while Veterinary careers scored the lowest (*M*=2.20, *SD*=1.00). The means and standard deviations of the Career Interest categories are presented in Table 4.10. Respondents were also asked (Yes=1/No=2/Not Sure=3) about their personal knowledge of professionals working in the STEM fields. These values were recoded as Yes=2/No=1/Not Sure=-99. Responses coded 'Not Sure' responses were excluded from further analysis. The results of this question are presented in Table 4.11.

Table 4.10

S-STEM Career Interest Scores

	M	*SD*	Min	Max
STEM Career Interest - Physics	2.75	0.91	1	4
STEM Career Interest – Environmental Science	2.40	0.89	1	4
STEM Career Interest – Biology/Zoology	2.51	0.99	1	4
STEM Career Interest – Veterinary Science	2.20	1.00	1	4
STEM Career Interest - Mathematics	2.82	0.95	1	4
STEM Career Interest - Medicine	2.58	1.00	1	4
STEM Career Interest – Earth Science	2.35	0.88	1	4
STEM Career Interest – Computer Science	2.79	1.01	1	4
STEM Career Interest – Medical Science	2.56	1.00	1	4

Table 4.10 continued

STEM Career Interest - Chemistry	2.82	0.92	1	4
STEM Career Interest - Energy	2.65	0.91	1	4
STEM Career Interest - Engineering	3.26	0.91	1	4

Table 4.11

S-STEM Knowledge of STEM Professionals Score

	M	*SD*	Min	Max
Knowledge of STEM Professional - Scientist	1.63	0.78	1	2
Knowledge of STEM Professional - Engineer	1.83	0.69	1	2
Knowledge of STEM Professional - Mathematician	1.57	0.77	1	2
Knowledge of STEM Professional - Technologist	1.71	0.84	1	2

STEM Major Intent

The S-STEM Survey instrument asked respondents to list the majors they were interested in for college; they were allowed to list three responses which were compared to those listed in the BLS Occupational Handbook and used to create the S-STEM Career Interest categories. Majors recognized within the STEM fields were coded as 'STEM' while other potential majors were classified as 'Non-STEM.' The majority of S-STEM respondents (83%) expressed interest in a STEM major, while the remaining 17% chose non-STEM majors (e.g., law, English). The results of this question are presented in Table 4.12.

Table 4.12

Distribution of S-STEM Respondent by Intended Major

	Frequency	Percent
Non-STEM Major	1,320	16.79
STEM Major	6,542	83.21

Level 2 Program Variables

Level 2 variables represent information that will be used in the school level of the mixed effects generalized linear model. The S-STEM data collects information labeling the outreach programs in which the respondents participated. Twenty-five individual programs were represented in the data, with more than half of respondents (54%) participating in the University's largest engineering summer outreach program. The rest of the participants were from a variety of programs both on campus and off-campus, and with areas of focus across the STEM spectrum. The full results of respondents' program participation are included in Table 4.13. Additionally, identifying labels for each program are provided in Appendix A.

Table 4.13

Distribution of S-STEM Respondents by Outreach Program

Program Code	Frequency	Percent
3	61	0.77
5	75	0.95
7	812	10.26
8	104	1.31
9	556	7.03
13	97	1.23

Table 4.13 Continued

14	259	3.27
15	65	0.82
16	2	0.03
18	28	0.35
19	187	2.36
21	1	0.01
22	4,288	54.20
24	22	0.28
25	18	0.23
26	96	1.21
29	81	1.02
31	808	10.21
32	58	0.73
35	94	1.19
37	67	0.85
38	17	0.21
40	35	0.44
41	18	0.23
188	63	0.80

School Type

Table 4.14

Distribution of S-STEM Respondents by School Type

	Frequency	Percent
Public School	6,122	77.87
Charter School	339	4.31
Private School	1,156	14.70
Home School	169	2.15
Other	76	0.97

Program Location and Title I Status

Table 4.15

Distribution of S-STEM Respondents by Geographic Locale

	Frequency	Percent
Rural	1,273	16.79
Urban	6,643	83.21

Note. N=7,916

The majority of S-STEM respondents (78%) attended public schools primarily in North Carolina, though programs existed in other states (e.g., Pennsylvania). Across these locales, 84% of respondents lived in areas considered urban by the National Center for Health Statistics Urban-Rural Classification system (Ingram & Franco, 2014). Also of note, slightly more than 4% of respondents attended charter schools, which like private schools often are run by boards or groups independent of governmental regulations, but similar to public schools provide non fee-based education to any student that attends. Additionally, the Title I status of the school attended by each respondent was measured. Nearly two-thirds (66%) of the respondents did not attend

Title I schools at the time they were administered the S-STEM survey instrument. Finally, a correlation matrix including the variables used for this analysis is presented in Appendix B.

Table 4.16

Distribution of S-STEM Respondents by School Title I Status

	Frequency	Percent
Title I School - Yes	2,478	34.44
Title I School - No	4,718	65.56

Statistical Analyses of the Research Questions

The results of this section will discuss the multilevel mixed effects model that was used to understand the factors that influence student STEM-self-efficacy. While this type of analysis cannot specifically state what causes students to lose or gain self-efficacy in STEM, or why students might choose a STEM major, it can outline the relationship between predictor variables and outcomes. Analysis of both research questions will begin with the null, or unconditional model, to examine the impact solely of program on self-efficacy in STEM and student intent to major in STEM. For Research Question One (RQ 1), the outcome variable (STEM self-efficacy) is continuous. Therefore, the mixed effects linear regression model will generate coefficients that relate to each variable's fit and influence on the model. Research Question Two has a dichotomous variable (STEM major intent) as the outcome variable. In this case, a mixed effect logistic regression model will be used. The logistic regression will generate odds ratios that measure the association between a variable and, in this case, one of the two possible outcomes (STEM major vs. non-STEM major). The odds ratios indicate how much more likely an outcome is based on the existing variable.

Collinearity in regression models can generate highly irregular results and is therefore critical to address. In the following analysis, issues of collinearity between the composite variable STEM Self-Efficacy and the individual constructs of the S-STEM survey (Science, Mathematics, and Engineering/Technology) were recognized in the initial analysis. In this case, for the analysis conducted for Research Question One, these independent variables were removed from the model. Collinearity results for RQ 1 are presented in Appendix C.

Variables with p-values lower than .05 were considered significant ($\alpha = .05$); as each stage of the model was analyzed, significant variables remained while non-significant variables were removed. The models were built in stages, beginning with an analysis of the effect of different programs on measured levels of STEM self-efficacy and reported major intent, respectively; in each case these served as the null models.

Additionally, the successive build of the models means that multiple comparisons between the variables will be presented. While this may increase the possibility of Type I errors in the analysis, the unique nature of this analysis, with this population, to measure the effect of each of these variables on STEM self-efficacy and STEM major intent made potential positive results more preferable than the potential loss of significant factors.

Results of Research Question One

What are the factors that influence student STEM self-efficacy?

a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and STEM self-efficacy?

b. What is the relationship between student level factors (e.g., race, gender, and age) and STEM self-efficacy?

c. Controlling for student-level factors, what is the relationship between program-level factors (program type, length, etc.) and STEM self-efficacy?

RQ 1a—The Unconditional Model

To answer this research question, each sub-question must be taken individually. To answer RQ 1a, the mixed effects model was generated with only Program as a level-2 factor. The results of this mixed effects regression for the unconditional model are presented in Table 4.17. In this model, the coefficient reported for Program accounts for the variance of the random effect that Program alone contributes to the model fit for the STEM Self-Efficacy outcome ($\beta = .06$, $p < .001$). While not large, this reveals that Program does positively account for some aspects of STEM Self-Efficacy. The interclass correlation (ICC) was also calculated as is presented in Table 4.17. The ICC represents the proportion of variance between each program at level 2 of the model. The ICC for the null model was 0.18, which indicates that 18% of the model variance in STEM self-efficacy is explained by program level factors.

Table 4.17

Summary of Mixed Effects Model Analysis of Program Effect in Predicting STEM SE

Predictors	ß	*SD*	*z*
Level 1			
Constant	3.98***	.05	78.20
Level 2			
Program	.06***	.02	

Table 4.17 continued

Parameters		
Level 1 Residual Variance	.25	.00
ICC	.18	

*$p < .05$, **$p < .01$, ***$p < .001$

RQ 1b—Demographic Variables

RQ 1b seeks to determine if there is a relationship with student-level factors and measures of STEM Self-Efficacy. In this build of the model, demographic variables such as gender, ethnicity or race, and grade level were added. Additionally, whether students were taking the survey before or after their outreach program was included in this block with the Pre-Post variable. Finally, dosage, or the number of times a respondent had participated in STEM outreach, was included as a categorical variable (low/medium/high). The results of this analysis are presented in Tables 4.18 and 4.19.

Table 4.18

Summary of Mixed Effects Model Analysis of Race and Gender in Predicting STEM SE

Predictors	ß	*SE*	z
Level 1			
Gender	-.16***	.01	-12.93
Race			
American Indian	-.27***	.04	-7.26
Asian	.01	.02	0.26
Black/African American	-.16***	.02	-9.41
Pacific Islander	-.15	.10	-1.48

Table 4.18 continued

Hispanic/Latino	-.12***	.03	-4.02
Multiracial	.01	.03	0.25
Other	-.08*	.03	0.25
Constant	4.27***	.05	-1.97
Level 2			
Program	.06***	.02	
Parameters			
Level 1 Residual Variance	.24	.00	

*$p < .05$, **$p < .01$, ***$p < .001$

Table 4.19

Summary of Mixed Effects Model Analysis of Demographics Block in Predicting STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.16***	.01	-13.04
Underrepresented/Overrepresented in STEM	-.13***	.01	-9.73
Pre-Post Intervention Status	.05***	.01	3.95
Grade Level	.02***	.02	5.30
Dosage Level	.13***	.02	7.22
Constant	3.91***	.07	57.33
Level 2			
Program	.06***	.02	

Table 4.19 continued

Parameters		
Level 1 Residual Variance	.24	.00

*$p < .05$, **$p < .01$, ***$p < .001$

Each of the level 1 variables in the model was significant ($p < .001$). Being female and being a member of a race or ethnic group traditionally underrepresented in the STEM fields both were negatively associated with higher levels of STEM self-efficacy. Respondents who took the survey after completing a STEM outreach program were more likely to have higher measures of STEM self-efficacy; students in higher grade levels were also more likely to have higher measures of STEM self-efficacy. Respondents who participated in more STEM outreach programs were associated with higher levels of STEM self-efficacy as well. More generally, there are factors of the model itself that must be considered: namely, are the assumptions for a mixed effects model being met as the successive models are built? Moving from the null model to the demographic block model the residual variance is fairly consistent, suggesting homoskedacity, and therefore supporting the validity of the model. While these results taken together mirror the findings from the literature review of this study and support the hypothesis of a relationship between student level factors and STEM self-efficacy, demographic variables are not the sole set of variables considered at the student level.

Other Student-Level Variables

The next set of variables at the student level included respondent's 21st century skills measurement. The 21st century skills category measured student self-reported belief in their levels of communication, collaboration, and critical thinking, and creativity. Next, measures of career interest by STEM category, students' future performance in science, mathematics, and

English/language arts in their upcoming coursework, and their knowledge of adults working in the STEM fields were added to the model. The results of this analysis are presented in Tables 4.20 through 4.23.

In this build of the model the previous demographic variables remain significant in addition to the 21st century skills attitudes measure. Higher self-reported measures of 21st century skills were positively correlated to higher measures of STEM self-efficacy. In fact, the 21st century skills measure had the largest impact in the model on self-efficacy compared to the other variables ($\beta = .52$, $p <. 001$).

The next build of the model represents the largest addition of variables at one time for any point of the model building process. Each of the career interest categories measured on the S-STEM instrument is represented by these variables, as presented in Table 4.21. In this build, respondent grade level becomes the only nonsignificant demographic variable.

Table 4.20

Summary of Mixed Effects Model Analysis of Demographics and 21st Century Skills Attitudes in Predicting STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.22***	.01	-21.81
Underrepresented/Overrepresented in STEM	-.13***	.01	-10.98
Pre-Post Intervention Status	.03**	.01	2.63
Grade Level	.01**	.00	2.53
Dosage Level	.08***	.02	5.49
21st Century Skills Attitudes	.53***	.01	55.22
Constant	1.90***	.07	28.43

Table 4.20 continued

Level 2		
Program	.04***	.01
Parameters		
Level 1 Residual Variance	.17	.00

*$p < .05$, **$p < .01$, ***$p < .001$

Table 4.21

Summary of Mixed Effects Model Analysis of Demographics Plus Career Interest in Predicting STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.06***	.01	-6.50
Underrepresented/Overrepresented in STEM	-.08***	.01	-8.33
Pre-Post Intervention Status	.03**	.01	3.79
Grade Level	.00	.00	.41
Dosage Level	.08***	.01	6.41
21st Century Skills Attitudes	.39***	.01	48.18
STEM Career Interest - Physics	.08***	.01	13.46
STEM Career Interest – Environmental Science	-.01	.01	-.68
STEM Career Interest – Biology/Zoology	.04***	.01	7.24
STEM Career Interest – Veterinary Science	-.04***	.01	-7.08
STEM Career Interest - Mathematics	.14***	.00	27.74
STEM Career Interest - Medicine	-.02**	.01	-2.58
STEM Career Interest – Earth Science	-.03***	.01	-4.90

Table 4.21 continued

STEM Career Interest – Computer Science	.02***	.01	4.22
STEM Career Interest – Medical Science	.03***	.01	4.49
STEM Career Interest - Chemistry	.05***	.01	8.82
STEM Career Interest - Energy	.01	.01	1.63
STEM Career Interest - Engineering	.16***	.01	26.85
Constant	1.12***	.07	28.43
Level 2			
Program	.01***	.00	
Parameters			
Level 1 Residual Variance	.11	.00	

*$p < .05$, **$p < .01$, ***$p < .001$

Each of the new variables represents a set of careers in STEM, initially developed from the BLS *Occupational Handbook,* that could be said to represent a defined branch of the STEM tree. The respondents were shown a definition of each category and provided a list of sample career fields. For example, the first category, Physics, listed the job 'physicist' as a potential career, but also included the related careers of 'astronomer' and 'aviation engineer.' The majority of potential careers are significant at the $p < .001$ level; the exceptions to this are 'Medicine,' which is only significant at the $p < .01$ level, and the career categories of 'Environmental Work' and 'Energy,' which are nonsignificant. Of the significant variables, the career categories of 'Veterinary Work,' 'Medicine,' and 'Earth Science' were all negatively associated with higher levels of STEM Self-Efficacy. In other words, as students' interest in

these careers rose, their measures of STEM Self-Efficacy tended to decrease. The remaining careers categories were positively correlated to STEM Self-Efficacy.

The future performance measures of the S-STEM instrument ask respondents to gauge how they expect to perform academically in their science, mathematics, and English/Language Arts coursework. The results from Table 4.22 indicate one change to the model. The career category 'Medicine' becomes significant at the $p < .001$ level, much like several of the career categories in the previous build. For the future performance measures, the first result of note is the lack of significance of 'English/Language Arts' in the model. Conversely, expected performance in both mathematics and science classes are significant ($p < .001$) and positively associated with higher levels of STEM Self-Efficacy. At this stage of the model, there is no significant relationship between their future performance in English and their level of STEM Self-Efficacy, while there is a positive relationship between their outcome expectancies for science and mathematics coursework related to STEM Self-Efficacy.

Table 4.22

Summary of Mixed Effects Model Analysis with Future Performance Variables in Predicting STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.04***	.01	-4.97
Underrepresented/Overrepresented in STEM	-.05***	.01	-6.10
Pre-Post Intervention Status	.03***	.01	3.63
Grade Level	.00	.00	-.44
Dosage Level	.06***	.01	5.28
21st Century Skills Attitudes	.32***	.01	40.57

Table 4.22 continued

STEM Career Interest - Physics	.07***	.01	12.62
STEM Career Interest – Environmental Science	-.01	.01	-1.13
STEM Career Interest – Biology/Zoology	.03***	.01	6.57
STEM Career Interest – Veterinary Science	-.03***	.01	-5.66
STEM Career Interest - Mathematics	.09***	.01	18.76
STEM Career Interest - Medicine	-.02***	.01	-3.46
STEM Career Interest – Earth Science	-.02***	.01	-3.48
STEM Career Interest – Computer Science	.02***	.00	5.69
STEM Career Interest – Medical Science	.03***	.01	5.22
STEM Career Interest - Chemistry	.04***	.01	7.26
STEM Career Interest - Energy	.02**	.01	3.00
STEM Career Interest - Engineering	.15***	.01	28.06
Future Performance - English	.00	.01	-.30
Future Performance - Math	.20***	.01	23.06
Future Performance - Science	.19***	.01	20.11
Constant	.51***	.05	10.38
Level 2			
Program	.00	.00	
Parameters			
Level 1 Residual Variance	.09	.00	

*$p < .05$, **$p < .01$, ***$p < .001$

The final set of student level variables added to the model asked respondents whether or not they had personal knowledge of someone working in the STEM fields. These results are

presented in Table 4.23. The demographic variables retain their same states of significance/nonsignificance as the prior build; additionally, the 'Environmental Work' career category and future performance for English/Language Arts also remain nonsignificant. Of the newly added variables, knowledge of adults working in technology careers was nonsignificant. However, knowledge of adults working in the remaining STEM categories were significant, albeit at different levels. Knowledge of adults working in science was significant (β = -.01, p < .01) and negatively associated with higher levels of STEM Self-Efficacy. Knowledge of adults working in engineering careers was also negatively associated with STEM Self-Efficacy (β = -.01, p < .05), while knowledge of adults in mathematics careers was the only category positively associated with higher levels of STEM Self-Efficacy (β = .01, p < .05). Taken together, these additional findings suggest that for RQ 1b, there is a relationship between demographics variables, and in many cases a variety of student level factors and STEM self-efficacy.

Table 4.23

Summary of Mixed Effects Model Analysis with Professional Knowledge Variables in Predicting STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.04***	.01	-4.83
Underrepresented/Overrepresented in STEM	-.05***	.01	-5.91
Pre-Post Intervention Status	.03***	.01	3.52
Grade Level	.00	.00	-.58
Dosage Level	.06***	.01	5.28
21st Century Skills Attitudes	.32***	.01	39.85
STEM Career Interest - Physics	.07***	.01	12.49

Table 4.23 continued

STEM Career Interest – Environmental Science	-.01	.01	-.96
STEM Career Interest – Biology/Zoology	.03***	.01	6.50
STEM Career Interest – Veterinary Science	-.02***	.01	-5.67
STEM Career Interest - Mathematics	.09***	.01	18.82
STEM Career Interest - Medicine	-.02***	.01	-3.41
STEM Career Interest – Earth Science	-.02***	.01	-3.56
STEM Career Interest – Computer Science	.03***	.00	6.03
STEM Career Interest – Medical Science	.03***	.01	5.16
STEM Career Interest - Chemistry	.04***	.01	6.97
STEM Career Interest - Energy	.02**	.01	3.03
STEM Career Interest - Engineering	.15***	.01	27.39
Future Performance - English	.00	.01	-.15
Future Performance - Math	.20***	.01	22.81
Future Performance - Science	.19***	.01	19.82
Knowledge of STEM Professional - Scientist	-.02**	.00	-3.09
Knowledge of STEM Professional - Engineer	-.01*	.01	-2.24
Knowledge of STEM Professional - Mathematician	.01	.01	2.05
Knowledge of STEM Professional - Technologist	.00	.00	-.74
Constant	.56***	.05	10.58

Table 4.23 continued

Level 2		
Program	.00	.00
Parameters		
Level 1 Residual Variance	.09	.00

*$p < .05$, **$p < .01$, ***$p < .001$

Simplifying the Model

A Wald test for interaction between the variables was conducted with the input variables of the model with the goal of simplifying the model; the results of these tests are presented in the Stata multilevel model results in Appendix D. Beginning with the nonsignificant terms, successive parametric tests checked for non-interactive variables. While in some cases these variables were significant in the model, when tested, each removed variable had no influence on the overall model fit. When complete, several variables could be successfully removed: Pre- or Post-survey status; Grade Level; Career Interest in Physics; Career Interest in Environmental Work; Career Interest in Medicine; Career Interest in Earth Science; Career Interest in Energy; Future Performance in English; and each of the Knowledge of Adults in STEM variables. The simplified model is presented in Table 4.24. For RQ 1c, the simplified version of the model was used in each successive build.

Table 4.24

Summary of Simplified Mixed Effects Model in Predicting Measures of STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.06***	.01	-7.20
Underrepresented/Overrepresented in STEM	-.06***	.01	-7.45
Dosage Level	.06***	.01	5.15
21st Century Skills Attitudes	.32***	.01	41.70
STEM Career Interest – Biology/Zoology	.03***	.01	6.28
STEM Career Interest – Veterinary Science	-.03***	.01	-6.77
STEM Career Interest - Mathematics	.10***	.01	21.77
STEM Career Interest – Computer Science	.03***	.00	6.89
STEM Career Interest – Medical Science	.02***	.00	3.82
STEM Career Interest - Chemistry	.06***	.01	11.81
STEM Career Interest - Engineering	.17***	.01	31.66
Future Performance - Math	.20***	.01	22.57
Future Performance - Science	.20***	.01	21.50
Constant	.56***	.04	12.75
Level 2			
Program	.00	.00	
Parameters			
Level 1 Residual Variance	.09	.00	

*$p < .05$, **$p < .01$, ***$p < .001$

Cross-Interaction Terms of the Model

Based on the body of prior research related to aspects of STEM self-efficacy, gender, and race, a series of cross-interaction terms were also built into the model. Specifically, the impact of gender and race on respondents' outcome expectancies was examined. In addition, the level of program participation, or dosage, was also included as a possible interaction term. When Gender was examined in the model for interaction with Future Performance in Science, Mathematics, and English/Language Arts, none of the terms were significant. However, for Race/Ethnicity, there were significant terms related to Future Performance in Mathematics. While in general, students with higher measures of future performance in mathematics were associated with higher levels of the STEM Self-Efficacy composite score, students underrepresented in STEM with similar levels of STEM Self-Efficacy as their peers expressed lower levels of Future Performance in Mathematics ($\beta = -.155$, $p < .01$). In other words, underrepresented students with similarly measured levels of STEM Self-Efficacy were less likely to think they would perform well in their mathematics courses. Interestingly, as these students' measures of future performance in math increased, they became more strongly associated with *lower* measures of STEM Self-Efficacy ($\beta = -.161$, $p < .01$).

Dosage level, or the number of times a respondent had participated in STEM outreach, was also examined for cross-term interaction with future performance. Dosage level produced significant cross-interaction terms with Future Performance in Mathematics; the 'medium' and 'high' dosage groups were more than twice as likely to be positively associated with higher levels of STEM Self-Efficacy ($\beta = .112$ vs. $\beta = .346$). The analysis also revealed that there were specific differences in the levels of dosage and their impact on measured STEM Self-Efficacy. Overall in the model, Dosage, grouped into three categories (low, medium, and high) was

significant and positively correlated to higher levels of STEM Self-Efficacy ($\beta = .06$, $p < .01$). However, when taken separately, the 'medium' dosage participant group was strongly negatively associated with STEM Self-Efficacy ($\beta = -.50$, $p < .001$), while the 'low' and 'high' groups remained positively associated with STEM Self-Efficacy.

RQ 1c—Program Level (2) Variables

RQ 1c seeks to determine the effect of program-level factors on the STEM Self-Efficacy measure. The variables at this level are associated with the programs in which the students were nested for the analysis. These variables include the type of school the respondents attend; the respondent's geographic area (rural vs. urban); and whether or not the respondent attended a Title I school. Each of the variables has a positively associated effect on measures of STEM Self-Efficacy. The results of this analysis are included in Table 4.25. While the model indicates an effect associated with the program level variables, it is important to note that it does not specifically show how these effects are influenced by specific categories of the individual variables. While the effects were measurable, when rounded to two digits the level 2 effects were effectively zero. Using the unrounded terms, the random effects of each level 2 variable were measured as ICC coefficients; for The ICCs of the program level variables were also calculated and are presented in Table 4.26. The effect of School type contributes 0.5% to the model, while Rural/Urban location and Title I status contribute 0.07% and 0.033% to the model, respectively. The analysis suggests that while small, each variable does contribute significantly to the model of STEM Self-Efficacy. Therefore, in answer to RQ 1c, program level variables do have a relationship to STEM Self-Efficacy, and for each variable, the relationship is positively correlated.

Table 4.25

Summary of Simplified Mixed Effects Model with Program-Level Effects in Predicting Measures of STEM SE

Predictors	ß	*SE*	*z*
Level 1			
Gender	-.05***	.01	-5.58
Underrepresented/Overrepresented in STEM	-.05***	.01	-6.21
Dosage Level	.06***	.01	5.24
21st Century Skills Attitudes	.32***	.01	40.11
STEM Career Interest – Physics	.06***	.01	11.96
STEM Career Interest – Biology/Zoology	.03***	.01	5.00
STEM Career Interest – Veterinary Science	-.03***	.01	-6.39
STEM Career Interest - Mathematics	.09***	.01	17.92
STEM Career Interest – Computer Science	.03***	.00	5.81
STEM Career Interest – Medical Science	.02***	.00	3.92
STEM Career Interest - Chemistry	.04***	.01	8.02
STEM Career Interest - Engineering	.16***	.01	27.62
Future Performance - Math	.20***	.01	21.68
Future Performance - Science	.19***	.01	18.68
Constant	.55***	.05	11.84
Level 2			
School Type	.00	.00	
Rural-Urban	.00	.00	
Title I Status	.00	.00	
Constant	.00	.00	

Table 4.25 continued

Parameters		
Level 1 Residual Variance	.09	.00

*$p < .05$, **$p < .01$, ***$p < .001$

Table 4.26

Intraclass Correlation of Program-Level Effects in Predicting Measures of STEM SE

	ICC
School Type	.005
Rural/Urban Geographic Area	.0007
Title I Status	.0003

Results of Research Question Two

What are the factors that influence student intent to major in STEM fields?

a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and intent to major in STEM fields?

b. What is the relationship between student level factors (e.g., race, gender, and age) and intent to major in STEM fields?

c. Controlling for student-level factors, what is the relationship between program-level factors (program type, length, etc.) and intent to major in STEM fields?

Understanding the factors that influence a student's intent to major in STEM is critical because prior research has shown that planned major is highly correlated to degree completion in the STEM fields (Maltese, 2008). Similar to Research Question One, the results of this section

will discuss the multilevel mixed effects model used to understand the factors that influence STEM major intent. While this type of analysis cannot specifically state why students might intend to major in a STEM field, it can outline the relationship between predictor variables and outcomes. For Research Question Two, the dichotomous variable STEM major intent is the outcome variable. Using a mixed effects logistic regression model, odds ratios were generated that relate the association between a variable and one of the two possible outcomes (STEM major vs. non-STEM major). The odds ratios indicate how much more likely an outcome is based on the predictor variable.

RQ 2a—The Unconditional Model

To answer RQ 2a, the mixed effects model was generated with only Program as a level-2 factor. The results of this mixed effects regression for the unconditional model are presented in Table 4.27. In this model, the coefficient reported for Program accounts for the variance of the random effect that Program alone contributes to the model fit for the major intent variable; since this value is greater than the p-value measured in the model, this variance is significant ($v = .73$; $p < .001$). This result shows that the program variable is positively correlated for some aspect of a student's intent to major in STEM, and therefore participation in STEM outreach does have a relationship with a student's intention to major in a STEM field. The interclass correlation (ICC) was also calculated as is presented in Table 4.27. The ICC represents the proportion of variance between each program at level 2 of the model. The ICC for the null model was 0.182, which indicates that 18.2% of the model variance in student intent to major in STEM is explained by differences in program.

Table 4.27

Summary of Mixed Effects Model Analysis of Program Effect in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Constant	4.28***	.83	7.49
Level 2			
Program	.73	.28	
Parameters			
Level 1 Residual Variance	.24	.00	
ICC	.18		

*$p < .05$, **$p < .01$, ***$p < .001$

RQ 2b—Demographic Variables

RQ 2b seeks to determine if there is a relationship with student-level factors and whether a student intends to major in a STEM field. In this build of the model, demographic variables such as gender, ethnicity or race, and grade level were added and presented in Table 4.28. Additionally, whether students were taking the survey before or after their outreach program was included in this block with the Pre-Post variable. Finally, dosage, or the number of times a respondent had participated in STEM outreach, was included as a categorical variable (low/medium/high). The results of this analysis are presented in Table 4.29.

Table 4.28

Summary of Mixed Effects Model Analysis of Race and Gender in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.65***	.04	-6.62
Race			
American Indian	.38***	.07	-5.64
Asian	1.16	.16	1.11
Black/African American	.61***	.06	-5.44
Pacific Islander	.25**	.12	-2.99
Hispanic/Latino	.58***	.10	-3.30
Multiracial	.78	.11	-1.74
Other	1.10	.27	.39
Constant	10.33***	2.39	10.10
Level 2			
Program	.81	.31	

*$p < .05$, **$p < .01$, ***$p < .001$

Gender, race, grade, and dosage are all significant predictors of student major intent ($p < .001$). Female respondents and respondents traditionally underrepresented in STEM are more than one-third less likely to say they will choose a major in the STEM fields. Further breakdown by racial and ethnic groups are presented in Table 4.28. Additionally, students are nearly 18% more likely to say they will major in STEM for each grade level they reach. Finally, increasing dosage is positively correlated to respondents being more likely to say they will major in a

STEM field; for each increase in dosage level (i.e., low to medium, medium to high) respondents are 28% more likely to say they intend to major in a STEM field.

Table 4.29

Summary of Mixed Effects Model Analysis of Demographics Block in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.65***	.04	-6.54
Underrepresented/Overrepresented in STEM	.62***	.05	-6.30
Pre-Post Intervention Status	1.01	.07	.19
Grade Level	1.18***	.02	8.35
Dosage Level	1.28**	.12	2.49
Constant	1.89*	.59	2.04
Level 2			
Program	.58	.23	

*$p < .05$, **$p < .01$, ***$p < .001$

Additional Student Level Variables

In the next model build, respondents' scores on the individual STEM constructs were added to the analysis. Being female and a member of an ethnic or racial group traditionally underrepresented in STEM remained significant and negatively associated with the intention to major in a STEM field. Increasing grade level also remained associated with a higher likelihood of choosing a STEM major. Higher mathematics self-efficacy, science self-efficacy, and engineering/technology self-efficacy construct measures were all significant and positively correlated to students being more likely to say they would major in STEM. Students with higher

measures in engineering/technology self-efficacy were 18% more likely to say they intended to major in STEM, while students with higher measures in mathematics were near twice as likely to say they would choose a STEM major, and higher measures of science self-efficacy were more than two and a half times more likely to be associated with respondent choosing a STEM field as an intended major. While measures of 21st century skills attitudes were also significant, they were negatively correlated to the intention to choose a STEM major. Respondents with higher measures of the 21st century construct were almost 40% less likely to say they would choose a STEM major. At this level of the model, dosage was non-significant but was left in future builds of the model for consistency. The full results of this analysis are presented in Table 4.30.

Table 4.30

Summary of Mixed Effects Model Analysis of Demographics and Attitudes Constructs in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.82***	.06	-2.53
Underrepresented/Overrepresented in STEM	.75***	.06	-3.42
Pre-Post Intervention Status	.93	.07	-.88
Grade Level	1.17***	.02	7.34
Dosage Level	1.04	.11	0.38
Mathematics Attitudes	1.92***	.10	31.13
Science Attitudes	2.54***	.15	15.97
Engineering Attitudes	1.18**	.07	2.77
21st Century Skills Attitudes	.62***	.05	-6.08
Constant	.01***	.01	-9.95

Table 4.30 continued

Level 2		
Program	.58	.23

*$p < .05$, **$p < .01$, ***$p < .001$

STEM Career Interest

Much like for RQ 1, the following build of the model is the largest addition of variables at one time for any point of the model building process. The results of this analysis are presented in Table 4.31. Each of the career interest categories measured on the S-STEM instrument is represented by these variables, as presented in the Table. In this build, whether a respondent took the survey before or after their outreach experience and dosage level remained nonsignificant demographic variables. Being female and a member of an ethnic or racial group traditionally underrepresented in STEM remained significant and negatively associated with the intention to major in a STEM field. Among the S-STEM constructs, higher measures of mathematics self-efficacy and science self-efficacy remained associated with a higher likelihood of choosing a STEM major, while 21st century skills measures remained negatively associated with choosing a STEM major. However, engineering/technology self-efficacy measures became non-significant in the model.

Table 4.31

Summary of Mixed Effects Model Analysis of Demographics Plus Career Interest in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.78**	.06	-2.97

Table 4.31 continued

Underrepresented/Overrepresented in STEM	.72***	.06	-4.03
Pre-Post Intervention Status	.95	.07	-.72
Grade Level	1.18***	.03	7.28
Dosage Level	1.06	.12	0.53
Mathematics Attitudes	1.72***	.11	8.32
Science Attitudes	2.34***	.15	13.09
Engineering Attitudes	.99	.08	-.00
21st Century Skills Attitudes	.61***	.05	-6.19
STEM Career Interest - Physics	1.03	.05	.53
STEM Career Interest – Environmental Science	.97	.05	0.53
STEM Career Interest – Biology/Zoology	1.07	.06	1.33
STEM Career Interest – Veterinary Science	1.05	.05	.97
STEM Career Interest - Mathematics	1.14**	.06	2.52
STEM Career Interest - Medicine	1.27***	.07	4.12
STEM Career Interest – Earth Science	.91	.05	-1.87
STEM Career Interest – Computer Science	.98	.04	-.45
STEM Career Interest – Medical Science	1.05	.06	.88
STEM Career Interest - Chemistry	1.00	.05	-.07
STEM Career Interest - Energy	.97	.05	-.51
STEM Career Interest - Engineering	1.29***	.07	4.41
Constant	.01***	.01	-9.67
Level 2			
Program	.26	.13	

*$p < .05$, **$p < .01$, ***$p < .001$

Compared to the STEM Self-Efficacy measure, the number of significant career interest variables are relatively low. Only Career interests in mathematics, medicine, and most interestingly, engineering were significantly associated with intending to choose a STEM major. Each career was positively correlated to a higher likelihood of intending to choose a STEM major; respondents with increasing interest levels in mathematics were 14% more likely to say they intended to major in STEM; respondents with increasing interest in medicine were 27% more likely to say they intended to major in STEM; and respondents with increasing interest levels in engineering were 29% more likely to say they intended to major in STEM.

In the next level of the model build, variables representing future performance in science, mathematics, and English/language arts coursework were added. The variables from the previous build remain unchanged in terms of association and significance. Of the three future performance variables, only future performance in science class was significant ($p < .001$); future performance in science was negatively associated with intention to choose a STEM major. Students who expected to perform well in their science coursework were almost 25% less likely to say they intended to choose a STEM major. The results of this analysis are presented in Table 4.32.

Table 4.32

Summary of Mixed Effects Model Analysis with Future Performance Variables in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.79**	.07	-2.87
Underrepresented/Overrepresented in STEM	.72***	.06	-3.98
Pre-Post Intervention Status	.94	.07	-.84
Grade Level	1.18***	.03	7.40

Table 4.32 Continued

Dosage Level	1.06	.12	0.47
Mathematics Attitudes	1.76***	.13	7.49
Science Attitudes	2.56***	.18	13.09
Engineering Attitudes	.99	.08	-.00
21st Century Skills Attitudes	.64***	.05	-5.38
STEM Career Interest - Physics	1.04	.05	.69
STEM Career Interest – Environmental Science	.97	.05	-.60
STEM Career Interest – Biology/Zoology	1.08	.06	1.50
STEM Career Interest – Veterinary Science	1.05	.05	1.03
STEM Career Interest - Mathematics	1.14*	.06	2.41
STEM Career Interest - Medicine	1.27***	.07	4.08
STEM Career Interest – Earth Science	.91	.05	-1.92
STEM Career Interest – Computer Science	.98	.04	-.36
STEM Career Interest – Medical Science	1.05	.06	.86
STEM Career Interest - Chemistry	.99	.05	-.24
STEM Career Interest - Energy	.98	.05	-.43
STEM Career Interest - Engineering	1.28***	.07	4.30
Future Performance - English	.89	.07	-1.50
Future Performance - Math	.98	.09	-.21
Future Performance - Science	.76*	.07	-3.00
Constant	.02***	.01	-8.53
Level 2			
Program	.25	.13	

*$p < .05$, **$p < .01$, ***$p < .001$

Respondent's personal knowledge of adults working in STEM was the last variable set added to the model for RQ 2b. The results of this analysis are presented in Table 4.33. Knowledge of adults working in science, engineering, and technology were all nonsignificant in the model. Knowledge of adults working in mathematics was significant ($p < .01$) and positively associated with intending to major in STEM. Respondents with knowledge of STEM professionals working in mathematics fields were 16% more likely to say they intended to major in STEM themselves. These findings suggest that for RQ 2b, there is a relationship between demographics variables, and other student level factors and a student's intent to choose a STEM major.

Table 4.33

Summary of Mixed Effects Model Analysis with Professional Knowledge Variables in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.79**	.07	-2.81
Underrepresented/Overrepresented in STEM	.72***	.06	-3.80
Pre-Post Intervention Status	.93	.07	-.87
Grade Level	1.18***	.03	7.18
Dosage Level	1.05	.12	0.47
Mathematics Attitudes	1.70***	.13	6.87
Science Attitudes	2.59***	.19	13.04
Engineering Attitudes	1.03	.08	.40
21st Century Skills Attitudes	.62***	.05	-5.57
STEM Career Interest - Physics	1.03	.06	.48
STEM Career Interest – Environmental Science	.98	.05	-.42

Table 4.33 Continued

STEM Career Interest – Biology/Zoology	1.06	.06	1.08
STEM Career Interest – Veterinary Science	1.06	.05	1.15
STEM Career Interest - Mathematics	1.16**	.06	2.71
STEM Career Interest - Medicine	1.27***	.07	4.04
STEM Career Interest – Earth Science	.90	.05	-2.07
STEM Career Interest – Computer Science	.97	.04	-.67
STEM Career Interest – Medical Science	1.05	.06	.88
STEM Career Interest - Chemistry	.98	.05	-.31
STEM Career Interest - Energy	.99	.05	-.21
STEM Career Interest - Engineering	1.25***	.07	3.77
Future Performance - English	.88	.07	-1.64
Future Performance - Math	.98	.09	-.25
Future Performance - Science	.76**	.07	-3.05
Knowledge of STEM Professional - Scientist	.97	.05	-.54
Knowledge of STEM Professional - Engineer	.92	.05	-1.49
Knowledge of STEM Professional - Mathematician	1.16**	.06	2.85
Knowledge of STEM Professional - Technologist	.98	.05	-.43
Constant	.02***	.01	-7.45
Level 2			
Program	.29	.14	

*$p < .05$, **$p < .01$, ***$p < .001$

RQ 2c—Program Level (2) Variables

RQ 2c seeks to determine the effect of program-level factors on a student's intention to choose a STEM field as their college major. The variables at this level include the type of school the respondents attend; the respondent's geographic area (rural vs. urban); and whether or not the respondent attended a Title I school; as in Research Question One, they remain associated with the programs in which the students were nested for the analysis. In the model, each of the variables has a positively associated effect on measures of a student's intent to major in STEM. The results of this analysis are included in Table 4.34. The random effects of each level 2 variable were also measured as ICC coefficients. The ICCs of the program level variables were also calculated and are presented in Table 4.35. The effects of School type and Title I status contributes what is functionally nothing to the model fit. Rural/Urban location contributes 7.4% of the variance to the model at the program level. The analysis suggests that the Rural/Urban geographical location variable does contribute significantly to the model of STEM Self-Efficacy. Therefore, in answer to RQ 2c, program level variables do have a positive relationship to a student's intent to choose a STEM major.

Table 4.34

Summary of Simplified Mixed Effects Model with Program-Level Effects in Predicting Student Intent to Major in STEM

Predictors	Odds Ratio	*SE*	*z*
Level 1			
Gender	.78**	.07	-2.73
Underrepresented/Overrepresented in STEM	.72***	.07	-3.60
Pre-Post Intervention Status	.92	.08	-.98
Grade Level	1.20***	.03	7.56

Table 4.34 continued

Dosage Level	1.08	.13	.66
Mathematics Attitudes	1.68***	.14	6.21
Science Attitudes	2.60***	.20	12.20
Engineering Attitudes	1.10	.10	1.10
21st Century Skills Attitudes	.63***	.06	-5.12
STEM Career Interest - Physics	1.03	.06	.43
STEM Career Interest – Environmental Science	.96	.06	-.70
STEM Career Interest – Biology/Zoology	1.08	.06	1.34
STEM Career Interest – Veterinary Science	1.03	.05	.62
STEM Career Interest - Mathematics	1.18**	.07	2.93
STEM Career Interest - Medicine	1.28***	.08	3.94
STEM Career Interest – Earth Science	.93	.05	-1.23
STEM Career Interest – Computer Science	.95	.05	-1.13
STEM Career Interest – Medical Science	1.03	.07	.44
STEM Career Interest - Chemistry	1.00	.06	.08
STEM Career Interest - Energy	.95	.06	-.82
STEM Career Interest - Engineering	1.23***	.08	3.36
Future Performance - English	.86	.07	-1.84
Future Performance - Math	.94	.10	-.57
Future Performance - Science	.74**	.07	-3.14
Knowledge of STEM Professional - Scientist	.99	.05	-.14
Knowledge of STEM Professional - Engineer	.95	.05	-.83
Knowledge of STEM Professional - Mathematician	1.16**	.06	2.66

Table 4.34 continued

Knowledge of STEM Professional - Technologist	.97	.05	-.60
Constant	.02***	.01	-7.39
Level 2			
School Type	.00[a]	.00	
Rural-Urban	.30	.00	
Title I Status	.00[a]	.00	
Constant	.18	.00	

[a] Note. Rounded values are approximately zero but unrounded values were used for additional analysis.
*$p < .05$, **$p < .01$, ***$p < .001$

Table 4.35

Intraclass Correlation of Program-Level Effects in Predicting Student Intent to Major in STEM

	ICC
School Type	.000
Rural/Urban Geographic Area	.074
Title I Status	.000

Random Effects by Program

Each multi-level mixed effects model included a level of analysis related to the effects of factors specific to the outreach programs in which students participated. However, while these random effects of the program level variables reiterated the connection between STEM outreach and factors that influence STEM persistence, in this case STEM self-efficacy and STEM major intent, they did not make a comparison between the individual programs. To do this, the posterior means related to the variance of each program were calculated by measuring their

specific random effects on each of these measures. The results of this calculation are presented in Figures 4.3 and 4.4; program codes are noted in Appendix A.

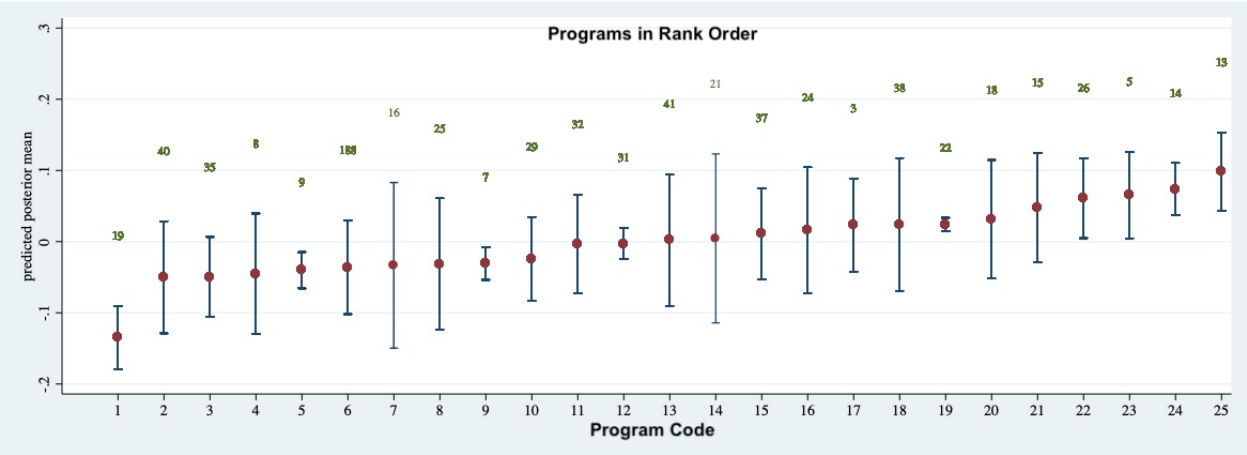

Figure 4.3 Random Effects of Program in Rank Order for STEM Self-Efficacy

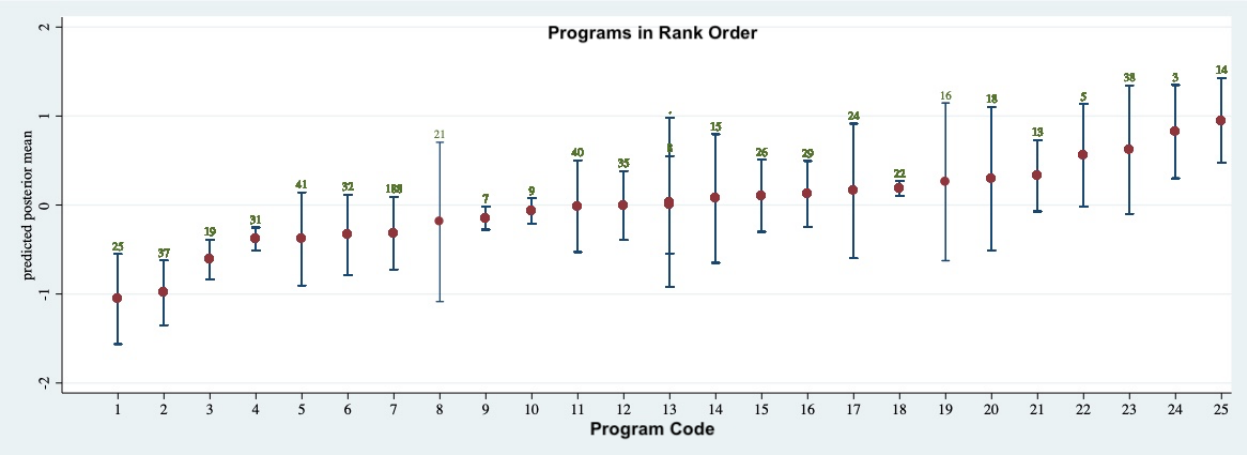

Figure 4.4 Random Effects of Program in Rank Order for Student Intent to Major in STEM

These program rankings show only the variance that Program alone adds to each measure. In both graphs, the highest ranked programs had a veterinary science focus. For STEM Self-Efficacy, the top two programs are veterinary science programs, one offered in a rural environment and the other offered in an urban space. Without knowing the individual curriculum of the programs, it is impossible to surmise why these specific programs seem to rank the highest among the programs examined, though this result will be examined in Chapter 5.

Summary of Findings

After a multi-level mixed effects model analysis of the factors that predicted STEM Self-Efficacy and a student's intent to major in STEM, findings revealed that there are a mix of variables that impact each of these measures, including: the specific outreach programs in which students participate, a series of demographic and person-level factors, and several variables associated with the programs themselves. Based on the values of the coefficients, 21st century skills, engineering career interest, and mathematics and science future performance were the strongest positive predictors of STEM self-efficacy. For intent to choose a STEM major, mathematics and science self-efficacy measures, interest in medical or engineering careers, and grade level were the strongest positive predictors, while measures of 21st century skills self-efficacy were the strongest negative predictors. The final chapter elaborates on key findings from the study, theoretical and practical implications of the mixed effects model analysis, future directions for research in STEM outreach and measures of self-efficacy, and study limitations.

Chapter Five: DISCUSSION AND CONCLUSIONS

The goal of this study was to examine the potential relationship between student-level and program-level factors and their impact on a student's measure of STEM self-efficacy and their intent to choose a STEM major in college after their participation in STEM outreach. Using two separate research questions as guideposts, two mixed effects model analyses were conducted as shown in Figure 5.1. In the first model, factors such as student demographics, measures of 21st century skill efficacy, and career interest were used as predictors of a student's STEM self-efficacy. In the second model, these same predictive factors, along with measures of separate science, mathematics, and technology/engineering self-efficacy attitudes, were used to examine a student's intent to major in a STEM field. These results will be discussed in the context of social-cognitive career theory (SCCT) along with the implications of these results and potential future considerations.

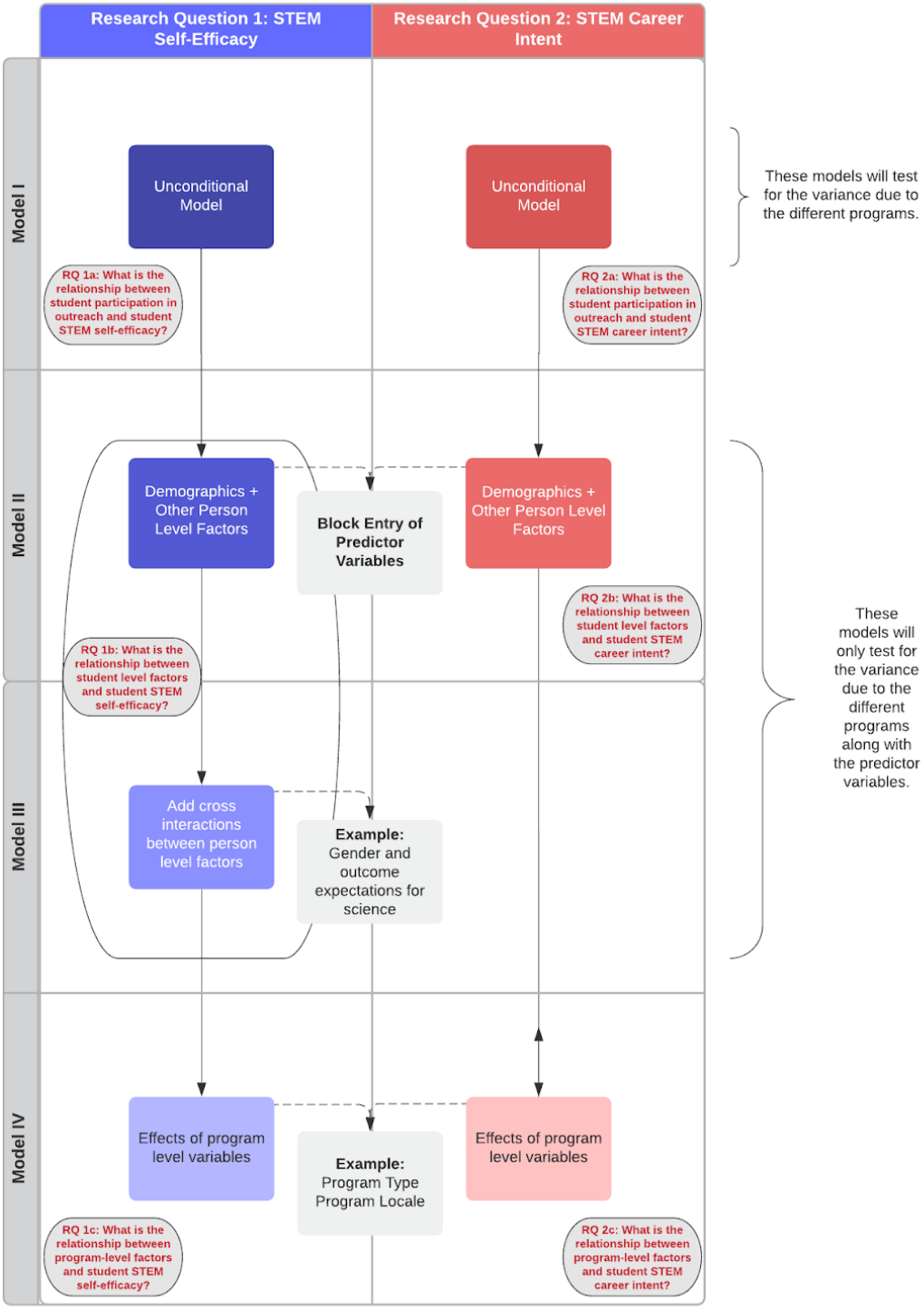

Figure 5.1 Flowchart of Progressive Model Building in MLM Analysis

When examined together, prior research of self-efficacy, outcome expectations, and career interest have shown positive relationships between these variables (Lent et al., 2010).

Participation in out-of-school, or informal, learning experiences, such as STEM outreach, is a contextual factor in the interactions models of how student career choice, as described in SCCT, is influenced by the constructs of self-efficacy, expectancy values, and motivation levels (Bandura, 1986; Eccles, 1994; Lent et al., 1994). A model of this set of relationships is presented in Figure 5.2. This study's specific focus was on determining the influence of this context (STEM outreach programs) on self-efficacy first, and then how both the informal learning context of the STEM outreach programs along with self-efficacy influence STEM major intent. Motivation is an aspect of the SCCT framework, but for this study, it was not analyzed.

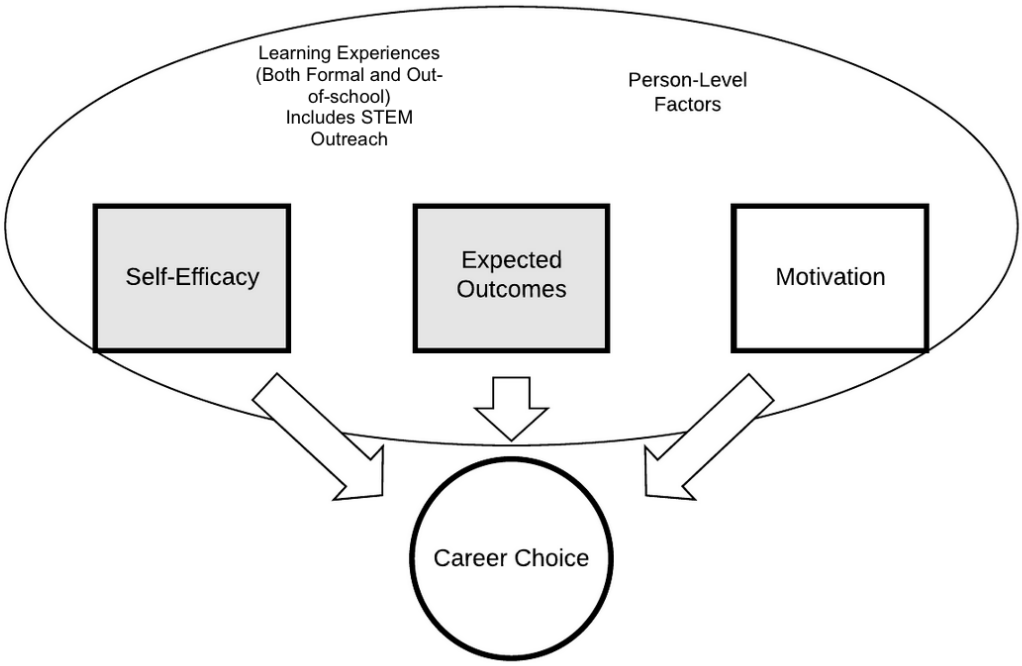

Figure 5.2 Model of Interaction between Self-Efficacy and Expected Outcomes on Career Choice, with study-specific factors shaded

Research Question One

The purpose of Research Question One was to determine which factors influence student STEM self-efficacy, particularly when they participate in STEM outreach. Three sub-questions were explored and will be discussed and explained here.

RQ 1a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and STEM self-efficacy?

At some level, each STEM outreach program examined in this study was designed to influence student attitudes positively toward STEM fields. While the programs were organized around a diverse set of STEM topics, the S-STEM assessment was designed to take a general measure of student attitudes, of which self-efficacy is a key component, toward STEM both before and after a STEM outreach intervention, regardless of the differences in the programs. In the first level of analysis, the unconditional model was explored to solely measure the impact of the varying programs in the study. While a multilevel analysis does not establish a causal relationship between variables, it can indicate a correlational relationship between measured variables; specifically, the unconditional model examines the relationship between the dependent variables of each research question (i.e., STEM Self-Efficacy and Intent to Major in STEM) and the impact of each outreach program. As noted in Table 4-17, the null model indicated that there is a positive relationship between program and self-efficacy in STEM as measured by the variance of the model due solely to program ($v = 0.06$, see Table 4.17.). The level of variance attributed to the Program variable in the model represented 18% of the total variance in the model.

These findings are supported by the research of Falk and Dierking (2010) and Hong and Milgram (2010), who found that outreach activities were associated with higher levels of interest and engagement, both characteristics related to self-efficacy. While prior research explored the effect of participation in STEM outreach and found that students who had outreach experience were more likely to have higher levels of STEM self-efficacy compared to peers without outreach experience, the same students showed little variability in efficacy from program to program (Weese, 2016). Additionally, these programs often incorporate mastery experiences that have been shown to increase STEM self-efficacy (Bandura, 1997; Betz & Schifano, 2000; Dunlap, 2005; Luzzo et al., 1999). For example, Luzzo and others measured self-efficacy in a series of math-related tasks constructed to be simple enough to insure that students would successfully complete them. After the student participated, half the group was told that completing the tasks was approximate to exhibiting higher math ability while the other half was told nothing. The researchers found that the students who were told that they experienced a specific intervention had greater increases in measures of self-efficacy than their peers, suggesting that the act of participating in a STEM outreach experience designed to promote positive self-perception of abilities can impact self-efficacy regardless of the specific learning outcomes of the experience.

RQ 1b. What is the relationship between student level factors (e.g., race, gender, and age) and STEM self-efficacy?

In the next progressive build of the multilevel model examining STEM self-efficacy, person-level factors were examined in the second model. RQ 1b sought to determine which person-level factors might influence student STEM self-efficacy. Many of the variables entered in the model were significant, including demographic characteristics such as race and gender.

While some previous studies may have suggested little relationship between these characteristics and STEM persistence (e.g., Maltese, 2008), the models of this study imply that student perceptions of their own STEM self-efficacy, which have been linked to persistence, are significantly impacted by both gender and race or ethnicity. Because of significant research and policy interest in broadening participation of underrepresented groups in STEM, race was specifically examined in two ways. First, students were categorized as either 'Overrepresented' or 'Underrepresented' if they described themselves as from racial or ethnic backgrounds more represented in STEM than their percentage makeup of the U.S. population, or less represented, respectively (Villalpando & Solórzano, 2005). In this case, underrepresented students were more likely to have lower measures of STEM Self-Efficacy compared to their overrepresented peers (ß = -.16, $p < .001$). When examined for distinct racial, ethnic, and gender groups, Black students, girls, and other groups traditionally underrepresented in STEM were more likely to have lower measures of STEM self-efficacy than their peers. In other words, race and gender were negative predictors of STEM self-efficacy. Specifically, students that identified as female (ß = -.15, $p < .001$), indigenous (ß = -.26, $p < .001$), Black (ß = -.16, $p < .001$), and Hispanic or Latino (ß = -.12, $p < .001$) were all less likely to have higher levels of STEM self-efficacy. This follows from previous research using SCCT; for example, Navarro et al. (2007) found that Hispanic and Latino students generally had lower measures of self-efficacy in science, while some researchers have noted that females have generally lower measures of STEM self-efficacy than their male peers (Painter, 2012). However, it should be noted that the participants in this study were on some level, self-selecting compared to the students involved in previous research. Often, this research has leaned on data from samples of students surveyed across the U.S. (e.g., Adelman, 2006; Maltese, 2008). As students who *chose* to participate in STEM outreach, it might be

expected that they would not follow the established trends for their measures of self-efficacy; that underrepresented students who have selected to attend STEM outreach programs would, generally, have higher self-efficacy and thus negating the difference from overrepresented groups. That they do suggests a deeper issue related to how demographics may factor into how students perceive their ability to succeed in STEM-related activities (Martin & Scott, 2014).

Another consideration is the cataloging of race and ethnicity for the purposes of understanding which students stay in and leave STEM fields. In several prior studies that found no significance for race or ethnicity in terms of STEM self-efficacy, ethnic and racial groups were treated as fully differentiating factors. While the differences in students based on race or ethnicity are profound, many of the challenges faced by students underrepresented in STEM are the same: a lack of quality STEM experiences (Betz, 2007), a lack of opportunity for the early development of mathematics skills (Moakler & Kim, 2014), and a lack of support from their families (Navarro et al., 2007). Examining this group of students holistically, as was attempted in this current study, provided a clearer picture of the dynamics of race and ethnicity in measuring STEM self-efficacy.

Gender also was a significant factor in the measure of STEM self-efficacy, as is consistent with SCCT research (Tsai & Tsai, 2010). Girls in STEM have often been measured with lower levels of self-efficacy as it relates to their STEM abilities in academic spaces (Zeldin & Pajares, 2000). The so-called "confidence gap" in male and female students can often explain the differences in their measures of self-efficacy (Klein et al., 1994). Some researchers have posited that this gap is exacerbated by participation in outreach activities because males are more likely to take advantage of these opportunities (Jones et al., 2000). In this study, male participants outnumbered females, even given that many of the programs evaluated had

recruitment of female participants as one of their program goals. These findings suggest that programs may need to do even more to change how they are perceived by female participants if they want to attract girls and succeed at improving their measures of STEM self-efficacy (Wang & Degol, 2017).

For temporal effects, three different examples are present in this study. Differences in the results before and after the interventions were significant in the model before simplification. Ideally, STEM outreach interventions would positively impact student levels of STEM self-efficacy, though the difference was so small that when simplified, the variable was dropped from the final model. While much of the work measuring STEM self-efficacy is done with high school or college students, others have suggested that the disparities we see in terms of STEM persistence have their roots in attitudes towards STEM formed as early as elementary school. Previous research has suggested that STEM self-efficacy decreases as students progress through school and stabilizes during high school (Wiebe et al., 2018). In this current study, however, grade level was nonsignificant in measuring levels of STEM self-efficacy, a surprising result given that researchers have documented how future STEM prospects for students evolve and change as students age (Sadler et al., 2012). This effect is also seen in data that would not traditionally be classified as longitudinal, such as the data from this study; so, while definitive conclusions related to ageing and the factors that affect STEM self-efficacy cannot be drawn, there do seem to be significant cross-sectional trends related to these factors (Denissen et al., 2007). However, as is the case with several other factors in this study, the self-selecting nature of outreach participants may already signal a level of interest and focus related to STEM different from their non-outreach participant peers. However, dosage, or the number of times a student participates in STEM outreach, signifies repeated participation in STEM interventions, which

has been suggested as a method for increasing STEM persistence (Prieto-Rodriguez et al., 2020). The results of our study are in line with Prieto-Rodriguez, as dosage was significant and positively correlated with increased measures of the STEM Self-Efficacy composite score ($\beta = .13$, $p < .001$; Table 4.19).

21st Century Skills

Factors such as math and science achievement have been studied for how they are influenced by STEM self-efficacy (Maltese, 2008; Mau, 2003). However, the goal of outreach is often not aligned with academic achievement objectives and instead is looking at student non-cognitive attitudes as measured in relationship to self-efficacy. It follows that the pedagogical approaches in these outreach opportunities often lean more heavily on STEM practices aligned with 21st century skills, rather than content knowledge. The remaining S-STEM sub-scale, 21st century skills, or the skills often identified as being crucial for workplace success in modern society, was found to be significant and positively associated with higher levels of STEM self-efficacy. When compared to the other statistically significant factors for STEM Self-Efficacy, 21st century skills had the largest effect size ($ES = .234$), and was twice as strong as the next strongest factor, engineering career expectations ($ES = .103$). Appendix E details the effect sizes for the other significant factors of the STEM Self-Efficacy variable. 21st century skills have been connected in prior research to increased interest in pursuing STEM careers (Brand , 2008; Ivey & Quam, 2009) when students participate in informal STEM activities, and the results of this study suggest that higher levels of 21st century skills correlate with higher levels of STEM self-efficacy, a factor also linked to STEM careers and persistence. Informal experiences are often specifically aligned with 21st century skills in part because of the value that these skills have in the modern STEM workforce and perceived interest of students in engaging such practices. This

intentionality may explain the comparatively larger effect size of the 21st century skill construct in this model.

Career Interests

The career interest indicator variables were designed to gauge participants' interest in one of 12 different categories of potential STEM fields as defined by the Bureau of Labor Statistics Occupational Handbook (U.S. Bureau of Labor Statistics, 2011). Several interesting results emerged from the analysis. The majority of the 12 categories were significant in the model; these results align with previous research that has shown that STEM career interest can be moderated by levels of STEM self-efficacy (Beier et al., 2019; Blotnicky et al., 2018). Of note, the career interest categories 'Environmental Work' and 'Energy' were not significant in the model. These two categories may be nebulous enough that participants are unable to form strong opinions related to their future interests. For example, while previous work has found that interventions specifically designed to improve student attitudes toward environmental work can be successful, the majority of the programs in this study developed and disseminated a more generalized, interdisciplinary approach to STEM content that may not be enough to change how participants respond to these emerging career areas (Carrier, 2007). Career paths involving work related to the environment, sustainability and energy are generating considerable interest with college students but may not yet have impacted younger populations or not be perceived as being aligned with STEM (Fecht, 2020).

Of the career interest categories that were significant, 'Veterinary Work' and 'Earth Science' were significant and negatively associated with the STEM Self-Efficacy variable. In previous research, these two career interest categories suffered the largest drops in interest from students when measured from the elementary to high school levels (Unfried et al., 2014). This

would seem to suggest that by the high school level, only students truly interested in pursuing these fields as careers would express that interest when asked, so the 373 veterinary outreach participants in this study may skew heavily in terms of their response since they are predominantly high school aged. But why would that continuing interest not translate into higher levels of measured STEM self-efficacy? In the case of veterinary work, the answer may lie in understanding how students participate in such outreach experiences. Peterson (2018) found that students' perception of veterinary work is lower for students who have participated in design-based outreach versus outreach centered purely around scientific inquiry. The majority of experiences expressly designed to promote veterinary careers fall into the design-based category where students are solving problems similar to those of professions in the field. This experience, more tightly aligned with veterinary careers and developed through repeated participation, may actually serve to both refine and reduce self-report measures of STEM self-efficacy; as the students become more familiar with the actual tasks that veterinary professionals perform, they become more aware of the areas where they need improvement to succeed in the career. These results are directly related to increased knowledge of STEM careers, which has been linked to STEM career choice (Zhang & Barnett, 2015).

The career interest category most strongly associated with higher levels of STEM self-efficacy was 'Engineering.' While K-12 STEM outreach is offered with a variety of disciplines as the focus, engineering as a cross-cutting concept appears in many of these interventions (Beeman-Cadwallader et al., 2012; Chen et al., 2011). Previous research has shown that applied engineering or engineering design is often a key part of STEM outreach. Additionally, research experiences in engineering have been shown to positively impact measures of STEM self-efficacy (Carter, 2011; Innes et al., 2012). These results align with prior research on self-efficacy

in students participating in informal STEM experiences that showed higher levels of self-efficacy in participants versus non-participants (Fantz et al., 2011). While many of the career interest categories are significant in the model, the effect level for the majority of categories is considerably weak. Referring back to SCCT, self-efficacy is a measure related to a sense of one's own abilities, and in these terms, student interest in certain fields may be related to the idea that one *could* perform in a specific career, though they may not necessarily be interested in pursuing it. This might explain the weak association between STEM Self-Efficacy and the career interest predictors.

It is possible that the same mechanism that leads participants to negatively associate veterinary and earth science-based experiences with STEM self-efficacy also mediates the positive connection between engineering and STEM self-efficacy. The underlying cause in all three cases could be related to the level of specificity of practices implied by the outreach interventions in each field. While engineering outreach is often a space for generalists testing the STEM waters to find a potential career, veterinary work and earth science are more well-defined and may attract students that are already leaning toward a potential career choice. These students are then more likely to think of their outreach experience as a proving ground of sorts, where any failure aligns to a skill deficit for that specific career. Conversely, the general nature of engineering outreach, often designed specifically to increase career interest and awareness--not to serve as a career preview--presents greater opportunities for positive impacts on STEM self-efficacy.

Future Performance and STEM Professionals

The future performance variable measures how participants expect to perform in their upcoming mathematics, science, and English or language arts coursework. Maltese (2008) found

that student confidence related to STEM academic performance was significantly associated with higher levels of STEM persistence and measures of STEM self-efficacy, a result confirmed by this study. Future performance in English was not significant; previous research has found a connection between learning English and science self-efficacy (Sandilos et al., 2020), however a direct connection between English performance and science self-efficacy, and STEM self-efficacy more generally, has not been thoroughly researched. This is perplexing since participants associate the 21st century skills measure with the STEM Self-Efficacy variable, but do not seem to link those skills, which include communication, to their English/language arts coursework. The results of this study also showed a significant positive relationship between mathematics and science future performance and STEM self-efficacy. Interestingly, in one study of early grade students, researchers found that measures of English and mathematics self-efficacy followed the same developmental trajectories and increased over the course of several years (Phan, 2012). While this may not confirm a relationship between English and mathematics self-efficacy, it suggests that the collective experiences of students may influence them both. However, it should be noted that Phan's measures of self-efficacy were associated with direct measures of performance, such as equating good grades with self-efficacy, something not replicated in this work and generally less prevalent in STEM outreach.

When asked about their knowledge of STEM professionals, students positively associated knowledge of adults in mathematics careers with STEM self-efficacy. Previous research has shown that for underrepresented students, mentoring can play a role in increasing student measures of STEM self-efficacy (MacPhee et al., 2013; Robnett et al., 2019). As students matriculate toward choosing a STEM career or not, having access to professionals in the fields they are considering can reduce the negative perceptions that are often formed by students in

middle and high school (Slovacek et al., 2012). Conversely, students negatively associated knowledge of science and engineering professionals with the STEM Self-Efficacy variable, a factor potentially explained by the narrow views many students hold in what careers qualify as 'STEM.' (Archer et al., 2014; Byars-Winston, 2014). These analyses demonstrate that there is worthwhile effort in both cultivating student aptitude in STEM subjects in school and developing a deeper understanding of potential STEM careers during informal STEM experiences since these factors are associated with STEM self-efficacy, and STEM persistence.

RQ 1c. What is the relationship between program-level factors (program type, length, etc.) and STEM self-efficacy?

In the model of STEM Self-Efficacy, the random effects, or variance, that was solely due to differences in specific outreach programs was measured. While each of the variables, school type, geographic area, and Title I status of the participants' schools, was significant and contributed measurably to the model, the level of contribution was exceedingly low for each variable (.005%, .0007%, and .00033%, respectively). The relevance of school type (e.g., public versus private) may require additional analysis to fully understand. For example, understanding a school's commitment to higher level math and science courses, or their connection to local STEM career pathways may play a role in developing their students' senses of STEM self-efficacy. Geographic area has been identified previously as a factor in predicting self-efficacy and STEM career intent (Tobin, 2008). In previous research, SCCT suggested that self-efficacy was associated with socioeconomic levels, however, this work specifically looked at students in formal learning environments (Shea et al., 2009). The context of this study population may be the factor that limits each of these variable's effects; the self-selected STEM outreach

participants of this study may have already mediated the program level factors examined in this model.

Research Question Two

The purpose of Research Question Two was to determine the factors related to student intent to major in STEM fields for those who participate in STEM outreach. SCCT theory predicts that career interest (intent) has a direct connection to future career choice. Career intent for STEM has been has been identified as a strong indicator of whether a student will actually choose a STEM major, matriculate through college, and enter a STEM career (Maltese, 2008), though few studies have measured the factors related to this interest in STEM fields (e.g., Kier et al., 2014). Using the categories of the S-STEM instrument, it is possible to discuss the factors related to career intent measured in this study. While no regression analysis can determine direct causality between factors, establishing a significant relationship between the variables is a worthwhile task. For answering Research Question Two, the odds ratio, or the measure of how likely an outcome is based on a factor, is used to examine the relationship between the factors (Hosmer et al., 2013). In this discussion, the dichotomous nature of the career intent variables is used, i.e., STEM versus non-STEM in the choice of a college major.

RQ 2a. What is the relationship between a student's out-of-school learning experiences (participation in outreach programs and extracurricular science activities) and student intent to major in STEM fields?

The context of informal learning experiences, specifically STEM outreach program participation as measured in this study, were significant and positively associated with higher levels of STEM career intent. While there was no non-participatory control group to compare against, it was still possible to measure how much variance the Program variable had in the

overall model. Program, along with its associated variables, was responsible for 18% of the variance of the STEM career intent factor. This would seem to indicate that while, generally, informal STEM experiences are beneficial to students, what a program offers in the way of experiences matters. As discussed in Chapter 4, when the variance of each program is examined, a relational scale can be developed that shows the relationship of that variance with positive or negative effects on STEM career intent. When examined, the model of the program rankings presents several interesting results. Very few programs have a consistently positive impact on measures of STEM career intent in terms of their program rankings; these programs all provide informal experiences in the biologically-oriented STEM fields. However, the only significant biologically-oriented STEM factor in the model was 'Medicine' so it is challenging to draw conclusions based on this result.

Conversely, the factor connecting the programs that had a consistently negative impact on STEM career intent was location; in this case, all of those programs that were offered at satellite sites away from the university campus setting. This generates two interesting questions—does the general nature or topic of the STEM program matter in terms of effect on STEM interest? And, does it matter where these informal programs are offered? For example, is this effect a function of the specific programs offered at these satellite sites, or is it perhaps a function of the participants participating at these locations? Further study, both quantitative and qualitative in nature, would provide additional clarity on both questions. One final observation also merits discussion. When examining the similar scale of program rankings by variance for self-efficacy, only engineering and mathematics programs consistently raise both measures of STEM Self-Efficacy and the measure of a student's intent to major in STEM. These results seem to point to specific success in their outreach design unmatched by their peer programs that would

benefit from further investigation, while also highlighting the importance of both mathematics and engineering practices as valuable pedagogical tools for delivering STEM content, even in the outreach environment. Overall, variance at the program level was small, but that may mean that further research into level two factors is required; for example, the role of instructor quality or self-efficacy and how it influences the program could be explored.

RQ 2b. What is the relationship between student-level factors (e.g., race, gender, and age) and intent to major in STEM fields?

Race and Ethnicity

RQ 2b examined the same set of predictor variables (with the notable addition of the individual STEM area construct measures) as RQ 1a and modeled how they influenced student intent to major in a STEM field. Much like the Self-Efficacy model, a wide array of variables were significantly predictive of STEM major intent, and correspondingly, race or ethnicity were negatively associated with the intent to major in a STEM field. At a more general level, students from underrepresented racial and ethnic backgrounds were significantly less likely to say they intended to major in a STEM field ($OR = .72$, $p < .01$), contrary to previous studies involving major choice and race/ethnicity (e.g., Riegle-Crumb & King, 2010). This was also true for several distinct racial and ethnic groups, as students that identified as indigenous ($OR = .37$, $p < .001$), Black ($OR = .61$, $p < .001$), Pacific Islander ($OR = .25$, $p < .01$), and Hispanic or Latino ($OR = .58$, $p < .001$) were all less likely to say they intended to major in a STEM field. Given the self-selecting nature of the student sample in this study, it may seem surprising that these students held statistically lower STEM intentions. However, this result is supported by existing SCCT models of career intent, as prior research has shown that, for a variety of reasons,

underrepresented students typically have lower levels of STEM intent (Fouad & Santana, 2017; Navarro et al., 2007).

One subgroup to consider however, were students who identified as multiracial. Traditionally research has treated these students as underrepresented (Rainey et al., 2019); however, in terms of their measures of STEM Self-Efficacy, they appear to align more with their White and Asian peers. Interestingly, these results do not translate to their intent to major in STEM, where the model suggests they more closely align with their Black, Hispanic/Latino, and Native American peers. This suggests that other factors that align closer to internalized self-concepts may have an impact on measures of self-efficacy while having little influence on a student's intent to major in STEM and pursue it as a career. While choosing any specific race or ethnicity is an identity-defining action, selecting 'multiracial' is a very specific act of self-conceptualization that involves how a person sees themselves and how they decide to identify in certain contexts (Shih & Sanchez, 2009). Measuring a concept like self-efficacy requires an internal focus, while the choice of a career may present as an externally-oriented contextual situation; this may explain why a student identifying as multiracial views the concepts of self-efficacy and career intent in non-convergent ways.

Gender, Dosage, Grade Level, and Pre-Post

Gender was a significant predictor of STEM career intent, as students who identified as female were more than 30% less likely to say they intended to major in a STEM field in Model I ($OR = .64$, $p < .001$), and remained more than 20% less likely to say they would choose a STEM major in the final model ($OR = .78$, $p < .01$). Of the demographic characteristics measured in this study, gender was the strongest negative predictor of whether a student would choose a STEM major. These results are aligned with previous research that has shown that female students

generally have fewer positive STEM experiences than their male counterparts, which may mediate their intent to choose a STEM major (Archer et al., 2010; Brotman & Moore, 2008). These finding from a self-selected sample of female students seem to be in line with previous literature in a way that was unlike several of the earlier findings in this study. While this work was unable to examine gender as a factor in major or career choice when the STEM fields are categorized (i.e., biologically-oriented STEM versus the physical sciences and engineering), previous work has suggested when these careers are separated, differences may exist in female students' level of interest (Unfried et al., 2014). A categorical exploration of STEM major intent may provide further insight into these phenomena.

Dosage, or repeat participation, had no significant influence in the model of STEM major intent. It would seem to follow that dosage in self-selected STEM outreach programs would be naturally connected to intent to major in STEM; repeated participation suggests interest in a subject, and interest has been identified in some studies as the most important factor in STEM career intent (Beggs et al., 2008; Kuechler et al., 2009), and therefore repeated participation would generate higher levels of STEM career intent. However, continual enrollment appears to be a counterfactual point when considering major intent, at least in the case of interventions designed around a weeklong model, which describes the majority of programs in this study. In this case, a law of diminishing returns would seem to dictate that at a certain point, students are as convinced as they will become to either choose, or in some cases, not choose to major in a STEM field. In one study of STEM majors, many chose not to pursue further efforts in STEM outreach, even when offered, once they felt they had collected enough experiences to inform their future careers (Laursen et al., 2012). It is possible something similar is happening for students deciding whether or not to major in STEM.

The connection between grade level and STEM career intent also agrees with prior research; as students age, they become more aware of the requirements involved in engaging in and succeeding in a STEM career trajectory. Students still participating in STEM outreach programs at the secondary level generally have a stronger amount of agency in choosing these programs, and so participation at this level is more likely to be correlated with future STEM career intent. However, while increasing grade level positively correlated to intent to major in STEM, as noted for RQ 1, grade level is nonsignificant in measuring levels of self-efficacy. Interestingly, taking the survey after participating in STEM outreach did not produce a significant increase compared to taking the survey before participating. Students who took the assessment after the conclusion of their outreach experience showed no significant difference in their intent to major in STEM. STEM outreach programs are typically designed to increase student interest in STEM, a concept that has been linked to STEM self-efficacy (Tai et al., 2006) and more broadly, STEM persistence. While the programs used in this study were of varying lengths and levels of engagement, as stated previously, the majority were weeklong interventions. This may suggest two possible mechanisms. First, longer, continuous STEM experiences may be required to see an effect on career intent, whereas an effect on self-efficacy is easier to achieve and measure because of the contemporaneous nature of the intervention. Alternatively, instead of seeing these STEM outreach experiences as vehicles for *increasing* STEM interest and career intent, they can be evaluated as opportunities to *sustain* STEM interest and career intent in these students already highly likely to pursue STEM. The act of sustaining STEM interest can be seen as an equally valuable method of supporting STEM persistence.

STEM Constructs

Previous research has shown that participation in science and mathematics coursework is tied to the potential of entering STEM careers (Maltese, 2008). Analysis of the S-STEM data concurs with this result and extends the idea further: students who have developed higher measures of self-efficacy in science and mathematics are more likely to say they intend to major in a STEM field. This suggests that participation in science and mathematics outreach alone is not enough; it must be outreach that is intentional about increasing and sustaining student attitudes towards these fields. This does not seem to be true for student attitudes towards engineering and technology, where there is no statistical significance in the model. One potential explanation for this is the explosion of engineering design-focused outreach efforts and the inclusion of engineering design as a central focus of science-related learning standards (Hmelo et al., 2000; Pruitt, 2014). Students expect that any science or math related careers will necessarily include engineering and technology, making attitudes toward these fields less likely to be the deciding factor in whether or not to choose a STEM career.

Perhaps more interestingly, the results of the 21st century skills measure suggest that students with higher levels of these 'modern workforce' skills are 38% less likely to say they intend to major in a STEM field, in contrast to the positive association of these skills with STEM self-efficacy. Why would students connect these skills to STEM self-efficacy but not to their intent to major in STEM? One possibility is that these students have preconceived notions about the types of individuals that pursue STEM careers, believing them to be "loners" or "nerds," and therefore unlikely to also be strong in 21st century skills related to teamwork or communication (Endedijk et al., 2017; Miller, 2017). Alternatively, it may be that students see 21st century skills as unaligned with a future STEM career or, alternately, aligned with all modern career paths.

21st century skills have long been linked to careers in areas such as business or, more generally, to the concept of project-based work that is becoming more ubiquitous as the workforce evolves (Trilling & Fadel, 2009). The implementation of 21st century skills across the K-12 curriculum over the last twenty years may make it seem less directly connected to STEM than previous student populations have.

Career Interests

The S-STEM career interest section revealed that engineering, mathematics, and medicine were the only STEM career categories significantly associated with STEM major intent. Each of these career categories was positively correlated to higher levels of intent. Other traditional STEM career areas like physics, biology, chemistry, and computer science were not significant in the model. This may imply that for STEM career intent, the connection between career interest and major intent is less important than the identity characteristics typically associated with SCCT. Perhaps careers in fields with strong interdisciplinary connections are more likely to be associated with STEM major intent while other careers, seen more narrowly by students, are not significant. Students with higher measures of career interest in engineering were nearly 25% more likely to say they intended to major in STEM. Why then in the major intent model were engineering attitudes not significant? Recall first, that the attitudes measure for engineering is also tightly linked to technology, a field which this study has revealed is ambiguous to students. Additionally, it must be stated again that this group of students are self-selected for their respective outreach programs. They may already (particularly if they are repeat participants) have higher initial attitudes towards engineering in general because of their understanding of its value to pursuing a STEM career, causing issues of collinearity undetected by the mode. Or, as noted earlier with student views on 21st century skills, this may be an

example of how modern students have integrated the idea of engineering design more fully into their experiences across all subjects, not just STEM. However, experiencing a program designed to highlight specific jobs in STEM, and in this case, engineering, may have a more direct influence on their measures of engineering self-efficacy than their intent to major in an engineering field.

Future Performance and STEM Professionals

Future performance in science was the only outcome measure that was significant among the variables measured. Additionally, science performance was the only future performance variable significant across both models, asserting the significance of science to both STEM self-efficacy and intent to major in a STEM field. In the case of career intent, future science performance is positively associated with the STEM Self-Efficacy construct. This follows from previous research that found students who performed better in secondary science coursework were more likely to be confident about their STEM abilities (Maltese, 2008). However, future science performance is negatively associated with the STEM Major Intent variable ($OR = .73$, $p < .01$), with students who say they plan on doing "Pretty Well" in science coursework being 25% less likely to say they intend to major in a STEM field, and students who said they expected to do very well being 50% less likely to say they intend to major in a STEM field. These results generate further questioning: why would future performance in science courses positively correlate to STEM self-efficacy, while being negatively associated with intent to major in a STEM field? A possible reason is related to how students pursue STEM coursework. Maltese revealed that students with higher attitudes toward STEM typically take more rigorous science courses as they progress through school. More challenging coursework may lead these students to more cautiously pursue futures in STEM. So, while they are clearly interested in STEM as a

future career path, they become less likely to say they will major in a STEM field. Potentially the most perplexing issue presented by this is the lack of significance that future performance in English has on the model, similar to the results for the STEM Self-Efficacy variable. Students negatively associated 21st century skills to STEM career intent, but there is no significant association between STEM career intent and the English future performance measure.

Knowledge of adults working in STEM was only significant for students that identified knowing someone working in the mathematics field. Unlike several of the other factors that seem to point in different directions, mathematics attitudes, mathematics career interest, and knowledge of adults working in math all are positively associated with higher levels of intent to major in a STEM field. These results support previous research that found that informal mathematics experiences were positively associated with interest in STEM careers, and in some cases was a stronger indicator than interest or attitudes toward science (Dabney et al., 2012). Future exploration of this concept could examine how computational attitudes, which share concepts from both mathematics and computer science, might align with either mathematics or engineering in terms of how it impacts the measure of intent to major in STEM.

RQ 2c. What is the relationship between program-level factors (program type, length, etc.) and student STEM intent to major in STEM fields?

Program level factors were significant and positively associated with intent to major in STEM. However, there is a caveat to these results—because the School Type and Title I Status variables contribute so little to the model that when their ICC values are calculated they round to zero, suggesting that they are of little to no impact in the model. While this would seem to contradict past SCCT models, it may again be explained by the self-selected nature of the students participating in these programs, making these students less influenced by program level

effects. The factor that represents geographic area is the only program-level measure that contributes meaningfully to the model. These results, coupled with the earlier program rankings, suggest that the location of informal outreach experiences has an impact on the program effect of STEM self-efficacy and intent to major in STEM. In the past, research involving geographical location has focused on where the students are from, but some have suggested that the location of outreach experiences is also important to consider (Flash et al., 2017).

Summary

The decision on career by a student is framed by a countless number of choices and experiences. This is especially true for students that choose a career in STEM because of the rather pronounced public narrative that surrounds these areas: STEM professionals are critically needed, highly valued, and well-paid. This makes the mechanisms that influence a student to begin and persist in pursuing a STEM career critical to understand. In this study, the contextual experience of STEM outreach, along with measures of student STEM self-efficacy, were found to have a measurable relationship to choosing a career in STEM. This theory of action is informed by SCCT which suggests that informal learning experiences and self-conceptualization both influence future career intent (Lent et al., 1994; Schunk & Pajares, 2002). Stated plainly, participation in STEM outreach and higher levels of STEM self-efficacy are both factors positively associated with the act of choosing a future STEM career. The importance of a student stating that they intend to major in a STEM career has been identified by previous research as strongly linked to STEM persistence (Maltese, 2008). This relationship is not well-understood; the underlying factors and direction of influence have been left unexamined in previous research. However, this study has revealed that a wide array of variables, including person-level factors like race and gender, attitudes toward the STEM fields, and career interests, along with program

level factors such as the individual programs themselves and students' geographical location, all influence a student's measure of STEM self-efficacy and their intent to major in a STEM field.

Future STEM career intent is strongly associated with a number of factors, starting with the positive overall influence of participation in STEM outreach. At the same time, several factors were significant at the person-level. Consistent with prior literature, race and gender continue to be factors associated with STEM career intent, as White and Asian students were more likely to say they intended to major in STEM than their Black, Hispanic/Latino, and Indigenous peers. Additionally, female students were also significantly less likely to say they intend to major in STEM. Another person-level factor, age, revealed that older students were associated with higher levels of self-efficacy related attitudes toward science and mathematics, a result supporting the theory proposed by Bandura (1997) that older students are more cognitively capable of improving their self-efficacy (Chen & Usher, 2013).

Factors related to measures of self-efficacy were also revealed as significant factors in measuring levels of intent to major in STEM. For example, students with stronger attitudes towards mathematics were more likely to have higher levels of STEM Self-Efficacy, and relatedly, were also more likely to have higher levels of STEM major intent, reaffirming the deep connection between mathematics self-efficacy, STEM Self-Efficacy, and selecting a STEM major seen in seminal persistence research (cf., Betz & Hackett, 1983). Conversely, higher measures of 21st century skills were negatively associated with STEM major intent and positively associated with STEM Self-Efficacy, a result unseen in previous research that appears to suggest a difference in how students interpret these skills related to their potential STEM career versus their own sense of STEM mastery.

Perhaps the most interesting findings are regarding the specific career interests factors and their relationship to STEM Self-Efficacy and intent to major in a STEM field. Only three career interest categories were significantly associated with higher levels of STEM career intent: interest in mathematics, interest in medicine, and interest in engineering. All three career interest categories were positively associated with STEM major intent, meaning students interested in these careers were more likely to say they would choose a STEM major. While the cross-cutting nature of math and engineering may partly explain the positive association with STEM major intent, the relationship between the medicine career interest category and STEM career intent will require further investigation. For the STEM Self-Efficacy variable, the model tells a different story; the majority of the career interest categories were significantly associated with higher measures of STEM Self-Efficacy. It may be more interesting to note the categories that are *not* significant: physics, environmental work, medicine, earth science, and energy. Medicine is the outlier, but the rest of the careers fall into what might be called the "core STEM" category (Wiebe et al., 2018). This may indicate a difference in how self-efficacy is perceived in the core STEM fields compared to the biologically-oriented STEM areas.

Earlier, the program rankings based on the overall variance contributed to the model were discussed. These random effects were calculated for both the STEM Self-Efficacy and the STEM Major Intent measures, respectively. As noted previously, the only programs that overall contributed positively to the model were in the biologically-oriented STEM areas, specifically agriculture, veterinary medicine, and zoology. Conversely, the programs that overall contributed negatively to each of the measures of this study fit into two categories: engineering-based programs, and programming designed to be interdisciplinary, which often place engineering methods and the engineering design process as central pillars of their instructional model. What

can explain the polar nature of biologically-oriented STEM and engineering informal experiences in the models of STEM Self-Efficacy and STEM Major Intent? One potential factor is location; for example, are the biologically-oriented STEM programs offered in rural areas while the engineering programs recruit in urban areas, leading to differences in their student participants, program resources, instructors, and other factors? However, when examined, the programs do not seem to follow any patterns based on geographic location. Another possibility to explore is participant age. Engineering-based programming tends to recruit a wider age range of students, while the biologically-oriented STEM programs lean more heavily to students in grades 9-12. Self-selection plays an outsized role for high school STEM outreach participants who have more agency in their extracurricular choices and are more aligned with their potential future careers (Zhang & Barnett, 2015). This may suggest that specialization is an important aspect of STEM informal experiences as students age and become closer to selecting potential STEM career trajectories.

Taken together, the results of this study suggest that STEM outreach is positively associated with a series of factors that are themselves linked to higher levels of STEM persistence, and at the very least do not significantly harm student interest in STEM or STEM careers. The value of student intent to major in STEM has been supported by this research as well, and as a predictor that has in the past been strongly associated with persistence to STEM degrees (Maltese, 2008), shows the connection between student intent, persistence, and eventually pursuing a STEM career.

Implications and Future Research

The most straightforward recommendation this study can provide is that students should be encouraged to participate in STEM outreach experiences. Outreach efforts strengthen and

sustain student attitudes toward STEM and prepare them for potential careers in the STEM fields. Specifically, time spent outside of the formal classroom allows for unique real-world opportunities and collaborative moments. Universities in particular have a role to play, as the resources that can be accessed by programs hosted at universities often dwarf those available to teachers, K-12 schools, or afterschool programs. If participation in STEM outreach is aligned with STEM persistence, then it follows that funding for STEM outreach should also be increased. STEM outreach programs can be thought of having two roles in the STEM pipeline; students with outreach experiences are less likely to leave the pipeline, and in this way, outreach is a sealant against loss. However, outreach experiences can also serve as introductions to specific STEM careers, in which case outreach is an inlet for students who have left STEM pathways and want to return. However, it is important that the programs have clear goals about their focus since students, especially those participating early on in STEM outreach, seem to be less interested in specific STEM content and more attracted to the general STEM opportunities that are available. In particular, the data suggests that mathematics- and science-focused content should be emphasized more than engineering and technology because of the importance that students apply to those areas.

The very nature of the term "STEM outreach" seems counterintuitive since most programs, including the programs in this study, require students (or in some cases adults connected to the student) to self-select their participation. The data in this study reflect that self-selection through the positively skewed measures of STEM Self-Efficacy and the large number of students that say they intend to major in a STEM field. Even given this precondition, students of color and girls still have lower measures of STEM self-efficacy and less intention to major in STEM compared to their peers. Emphasizing the recruitment of underrepresented students is of

course not new; but programs must find novel methods of reaching these students and closing the gap between them and their peers. Prior research suggests that programs may look to earlier interventions as a possible solution (Tai et al., 2006), however further qualitative exploration of the specific factors that influence underrepresented students may be necessary. Additionally, aligning the goals of these programs with the social concerns and experiences of these students has proven to be the most effective method of increasing both their interest and self-efficacy in STEM (Zeldin & Pajares, 2000).

SCCT suggests that the relationship between an activity and its connection to students on a personal level plays an important role in whether or not students will associate the activity with positive outcome expectations (Lent et al., 1994). The results of this study show that students already align science and mathematics expectations with higher levels of STEM self-efficacy and greater intent to major in a STEM field. This positive relationship is also true of 21st century skills. Unfortunately, this does not extend to their expectation of future performance in English or language arts, though this coursework is often foundational to the '4Cs' of 21st century learning. Programs must more explicitly link the skills of communication, creativity, collaboration, and critical thinking to their science and mathematics content by creating opportunities for students to collaborate and share their experiences. Finally, SCCT predicts that knowledge of STEM professionals should influence student attitudes towards STEM; however, other than math, the data suggests little relationship between STEM self-efficacy or major intent and this knowledge. Programs, especially those hosted by universities, must leverage their resources to create connections between students and researchers. These more intentional experiences might reveal a stronger connection between knowledge of STEM professionals and STEM self-efficacy and major intent.

Several suggestions come to mind when thinking about how this research could be extended. First, it must be acknowledged that while the study looked at cross-interactions between self-efficacy, race, and gender, there are other potential areas for cross-interactions that might be explored. The career interest category, in particular, may be influenced by perceptions that are driven by cultural perspectives not revealed by S-STEM data. Secondly, given the early formation of STEM identities in students, longitudinal studies of how measures of STEM self-efficacy evolve over time and its relationship to major intent is recommended. Using existing research as a framework, studies like the High School Longitudinal Study (HSLS) (NCES, 2012) that already look at STEM persistence could be adapted to ask questions related to STEM self-efficacy, while distinguishing formal experiences from STEM outreach informal experiences. Finally, universities must place value on gathering rigorous data from their own existing STEM offerings. While intention to major in a STEM field is a useful tool for tracking the development of students at the elementary or secondary school level, once students matriculate that data becomes much less useful if it cannot be linked to actual student performance and persistence at the postsecondary stage. Universities must support their outreach efforts by allowing them to correlate existing university students to their previous STEM outreach experiences.

Quantitatively, the construction of each model of this study required several assumptions related to the development of each level of the model. First, the initial form of the models for STEM Self-Efficacy and STEM Major Intent both began with modeling the demographic variables of the program participants, as many of these variables have been explored in previous research and can be compared across studies. Next, the variables associated with the STEM constructs were added to the models because they seemed most related to building self-efficacy and persistence. The career interest variables were added next, and after reflection, it is possible

that these factors should have been added to the model before the STEM constructs. Future work could investigate whether the impact of these factors would change depending on when they were input into the model. The second-level variables related to the STEM outreach programs were the final variables input in the model. Further investigation could explore whether these variables are exclusively second level and related to the outreach programs, or possibly have influence at the person level.

Limitations

While the results of this study imply several relationships between predictors of STEM self-efficacy and student intent to major in STEM fields, these relationships merely show levels of correlation. With this type of analysis, making direct links between predictor variables and the dependent variables is not possible; while the data suggests that informal experiences like STEM outreach do influence STEM self-efficacy and STEM major intent, they do not necessarily cause a student to declare higher levels of self-efficacy or promise to major in, say, physics. There are also limitations related to the population of the study. While many participants in the STEM outreach efforts of the university are represented here, for most of the programs, participation in the survey was voluntary and therefore the data represents students (and their families) that were willing to participate—self-selection among students who *already* were self-selected. Conversely, there are students who were removed during the data cleaning process that were primarily single-time participants and may have provided more insight into how those students are influenced by participation in STEM outreach. Additionally, many of these programs target specific populations, creating a sample that is not fully representative of all U.S. students. Also, while the cross-sectional database used in this current work looks across grade levels, it lacks the statistical robustness of a true longitudinal study. Another limitation of this study relates to the

breadth of the STEM outreach programs being explored. The differences in each program in terms of what ages they reach, the topic areas, the instructors, and the length of the programs would have been difficult to measure and account for individually; that may require further research to disentangle. Future investigation should also examine grouping of the outreach programs based on their supposed area of impact, i.e., programs dedicated to biology versus those in areas such as physics or chemistry. Finally, there were factors that this study could not address because of the limitations of the S-STEM instrument itself. Previous literature has suggested that a wide array of variables unaccounted for could influence STEM self-efficacy or intent to major in STEM; parental aspirations, cultural perspectives, teacher practices, and instructional methodologies could all have an impact on these factors (cf., Beede, Julian, Khan, et al., 2011; Beede, Julian, Langdon, et al., 2011; Maltese, 2008). Only student data are included in this study; teacher and program data (other than that learned through participation in the S-STEM Survey) are not included. There may be teacher-related factors that predict STEM self-efficacy and STEM major intent; however, this data cannot be ascertained from the S-STEM Survey. The instrument may have also obscured certain aspects of STEM self-efficacy and major intent due to its very construction. The connected engineering and technology constructs may be watering down the influence of engineering-related predictors, which in most cases were shown to be fairly strong, while artificially increasing the influence of technology predictors that are relatively weak. Whether or not these constructs should remain coupled requires further study.

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APPENDICES

Appendix A

Additional Dataset Information

Program Codes with Descriptors

The programs evaluated in this study are represented in the data by code numbers instead of descriptors. A list of these codes matched with the descriptors is presented here. The descriptors follow a similar convention as the Career Interest categories of the S-STEM survey and are labeled according to the camp program's stated areas of STEM interest. Camps designed to introduce students to multiple STEM areas have been labeled as 'Interdisciplinary.'

STEM Outreach Descriptor	Program Code
Biology/Zoology Camp	3
Biology/Zoology Camp	5
Biology/Zoology Camp	35
Biology/Zoology Camp	41
Biology/Zoology Camp	188
Camp Specialty Not Specified	16
Chemistry Camp	32
Computer Science Camp	40
Earth Science Camp	26
Energy Camp	18
Energy Camp	19
Engineering Camp	22
Engineering Camp	29
Engineering Camp	31
Interdisciplinary Camp	7
Interdisciplinary Camp	8
Interdisciplinary Camp	9

Interdisciplinary Camp	24
Interdisciplinary Camp	25
Interdisciplinary Camp	37
Medical Science Camp	21
Physics Camp	15
Veterinary Camp	13
Veterinary Camp	14
Veterinary Camp	38

Unique Variables within the Dataset

For the purposes of this study, each survey response from the S-STEM survey instrument was treated as an individual data point. However, many students repeatedly participated in each STEM outreach intervention. A tabulation of the unique data points from this dataset are presented here.

Unique S-STEM Respondents

	Frequency	Percent
Respondents	4,543	100

Unique S-STEM Respondents by Gender

Gender	Frequency	Percent
Male	2,606	57.4
Female	1,934	42.6

Unique S-STEM Respondents by Grade Level

Grade Level	Frequency	Percent
3	3	0.04
4	10	0.13
5	51	0.65
6	939	11.94
7	1,269	16.14
8	1.221	15.53
9	825	10.49
10	831	10.57
11	1,230	15.64
12	1,448	18.42
13	36	0.46

Unique Race/Ethnicity for S-STEM Respondents by Overrepresented/Underrepresented in STEM Labels

Race Category in STEM	Frequency	Percent
Overrepresented	3,020	66.32
Underrepresented	1,534	33.68

Unique S-STEM Respondents from Counties or Districts with More Than 100 Participants

School District	Frequency	Percent
Wake County Schools	2,438	31.00
Chapel Hill-Carrboro City Schools	243	3.10
Nash-Rocky Mount Schools	243	3.10
Charlotte-Mecklenburg Schools	198	2.52
Durham Public Schools	195	2.48
Guilford County Schools	121	1.54
Johnston County Schools	114	1.45
Pitt County Schools	111	1.41

Unique S-STEM Respondents by Race/Ethnicity

Race/Ethnicity	Frequency	Percent
American Indian	118	2.57
Asian	395	8.59
Black/African American	905	19.68
Pacific Islander	17	0.37
White	2,625	57.09
Hispanic/Latino	193	4.20
Multiracial	232	5.05
Other	113	2.46

Unique S-STEM Respondent by Intended Major

	Frequency	Percent
Non-STEM Major	944	20.09
STEM Major	3,756	79.91

Unique S-STEM Respondents by Outreach Program

Program Code	Frequency	Percent
3	31	0.67
5	39	0.84
7	332	7.14
8	59	1.27
9	226	4.86
13	86	1.85
14	214	4.60
15	54	1.16
16	2	0.04
18	19	0.41
19	184	3.96
21	1	0.02
22	2,299	49.44
24	22	0.47
25	9	0.19
26	50	1.08
29	41	0.88
31	744	16.00
32	43	0.92
35	50	1.08
37	46	0.99
38	17	0.37
40	35	0.75
41	12	0.26
188	35	0.75

Unique S-STEM Respondents by School Type

	Frequency	Percent
Public School	3,561	77.70
Charter School	199	4.34
Private School	666	14.53
Home School	96	2.09
Other	61	1.33

Unique S-STEM Respondents by Geographic Locale

	Frequency	Percent
Rural	819	17.88
Urban	3,762	82.12

Unique S-STEM Respondents by School Title I Status

	Frequency	Percent
Title I School - Yes	1,395	34.32
Title I School - No	2,670	65.68

Appendix B

Correlation Matrix

Var #	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Math Attitudes	1.00													
2	Science Attitudes	0.38	1.00												
3	Engineering Attitudes	0.46	0.40	1.00											
4	21st Century Skills	0.38	0.44	0.42	1.00										
5	STEM Self-Efficacy Composite	0.80	0.75	0.79	0.53	1.00									
6	Dosage	-0.01	0.02	0.05	0.03	0.02	1.00								
7	Outreach Program	-0.06	0.00	0.01	0.00	-0.02	-0.11	1.00							
8	Pre-/Post	0.01	0.05	-0.02	0.03	0.02	0.10	0.01	1.00						
9	Grade Level	0.08	0.13	0.01	0.07	0.10	-0.12	0.11	-0.07	1.00					
10	School Type	-0.01	-0.03	-0.02	-0.04	-0.03	-0.07	-0.01	0.01	0.02	1.00				
11	Gender	-0.10	0.00	-0.27	0.11	-0.16	0.00	-0.07	0.01	-0.02	-0.01	1.00			
12	Over/Under-represented in STEM	-0.19	-0.14	-0.16	-0.02	-0.21	0.18	-0.16	0.04	-0.20	-0.11	0.06	1.00		
13	Race/Ethnicity	0.09	0.11	0.08	0.01	0.12	-0.13	0.08	-0.03	0.14	0.12	-0.07	-0.25	1.00	
14	Physics Career Interest	0.33	0.35	0.45	0.16	0.48	-0.05	0.00	-0.02	0.14	0.01	-0.21	-0.20	0.11	1.00
15	Environmental Career Interest	-0.04	0.14	0.02	0.11	0.05	-0.10	0.09	-0.02	0.04	-0.06	0.16	-0.08	0.06	0.19
16	Biology Career Interest	-0.15	0.17	-0.14	0.08	-0.06	-0.10	0.04	-0.01	-0.04	-0.05	0.23	0.02	0.00	0.00
17	Veterinary Career Interest	-0.18	0.04	-0.21	0.05	-0.15	-0.06	0.03	0.02	-0.16	-0.03	0.27	0.07	0.00	-0.11
18	Mathematics Career Interest	0.64	0.23	0.43	0.23	0.56	0.00	-0.03	0.01	0.05	-0.02	-0.15	-0.12	0.04	0.44
19	Medical Career Interest	0.02	0.16	-0.05	0.16	0.05	0.04	-0.08	0.03	-0.07	-0.02	0.20	0.12	-0.08	0.02
20	Earth Science Career Interest	-0.07	0.14	0.02	0.06	0.03	-0.01	0.05	0.01	-0.11	-0.06	0.05	0.01	0.03	0.16
21	Computer Science Career Interest	0.20	0.08	0.44	0.05	0.31	0.06	-0.06	-0.03	-0.19	0.00	-0.28	-0.02	-0.03	0.27
22	Medical Science Career Interest	0.04	0.23	0.01	0.16	0.12	0.03	-0.08	0.00	-0.03	-0.01	0.18	0.09	-0.06	0.08
23	Chemistry Career Interest	0.23	0.36	0.23	0.14	0.35	0.01	-0.02	0.00	-0.10	-0.02	-0.02	-0.03	0.04	0.39
24	Energy Career Interest	0.22	0.25	0.45	0.12	0.39	0.00	0.03	-0.03	0.01	0.00	-0.25	-0.11	0.08	0.48
25	Engineering Career Interest	0.40	0.23	0.71	0.19	0.57	0.04	-0.01	-0.03	0.01	0.00	-0.27	-0.16	0.07	0.44
26	English-Future Performance	0.09	0.18	0.07	0.27	0.14	0.03	-0.04	0.02	0.06	-0.06	0.13	-0.01	-0.01	0.02
27	Mathematics-Future Performance	0.69	0.20	0.29	0.24	0.52	-0.01	-0.03	0.01	0.10	-0.02	-0.09	-0.15	0.06	0.23
28	Science-Future Performance	0.30	0.48	0.23	0.24	0.43	-0.02	0.02	0.01	0.12	-0.03	-0.07	-0.15	0.11	0.22
29	Mathematics-Advanced Coursework	-0.42	-0.14	-0.18	-0.13	-0.32	-0.02	0.08	0.03	-0.17	0.03	0.05	0.11	-0.02	-0.19
30	Science-Advanced Coursework	-0.16	-0.38	-0.13	-0.15	-0.29	0.01	0.00	0.02	-0.21	-0.01	0.01	0.10	-0.04	-0.17
31	Engineering-Advanced Coursework	-0.26	-0.18	-0.42	-0.12	-0.37	-0.03	0.04	0.03	-0.06	0.02	0.20	0.07	-0.04	-0.23
32	STEM Major/Non-STEM Major	0.27	0.27	0.20	0.09	0.31	-0.03	-0.04	-0.02	0.16	0.01	-0.08	-0.14	0.08	0.16
33	Known Adults-Scientists	-0.05	-0.15	-0.06	-0.08	-0.11	-0.03	0.03	-0.01	-0.09	0.00	-0.01	0.04	0.01	-0.09
34	Known Adults-Engineers	-0.15	-0.12	-0.17	-0.13	-0.19	0.01	0.01	0.04	-0.15	-0.03	0.06	0.08	0.00	-0.13
35	Known Adults-Mathematicians	-0.04	-0.03	-0.05	-0.11	-0.05	0.00	0.01	0.00	-0.03	0.00	0.00	-0.05	0.04	-0.03
36	Known Adults-Technologists	-0.04	-0.05	-0.10	-0.07	-0.08	-0.05	-0.01	-0.02	0.02	0.03	0.06	-0.03	0.04	-0.07
37	Rural/Urban Status	0.03	0.01	0.07	-0.02	0.05	-0.07	-0.08	-0.03	-0.06	-0.01	-0.01	-0.05	0.04	0.06
38	Title I School Status	-0.06	-0.08	-0.06	-0.04	-0.08	0.15	0.02	0.05	-0.17	-0.30	-0.02	0.21	-0.09	-0.11

Var #	Variable	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	Math Attitudes														
2	Science Attitudes														
3	Engineering Attitudes														
4	21st Century Skills														
5	STEM Self-Efficacy Composite														
6	Dosage														
7	Outreach Program														
8	Pre-/Post														
9	Grade Level														
10	School Type														
11	Gender														
12	Over/Under-represented in STEM														
13	Race/Ethnicity														
14	Physics Career Interest														
15	Environmental Career Interest	1.00													
16	Biology Career Interest	0.50	1.00												
17	Veterinary Career Interest	0.32	0.60	1.00											
18	Mathematics Career Interest	0.03	-0.11	-0.13	1.00										
19	Medical Career Interest	0.14	0.35	0.37	0.06	1.00									
20	Earth Science Career Interest	0.53	0.42	0.28	0.04	0.19	1.00								
21	Computer Science Career Interest	-0.11	-0.16	-0.15	0.32	-0.05	0.03	1.00							
22	Medical Science Career Interest	0.20	0.38	0.33	0.06	0.80	0.20	-0.01	1.00						
23	Chemistry Career Interest	0.18	0.20	0.08	0.33	0.28	0.27	0.18	0.34	1.00					
24	Energy Career Interest	0.23	0.01	-0.09	0.33	0.01	0.27	0.32	0.08	0.44	1.00				
25	Engineering Career Interest	0.01	-0.18	-0.24	0.45	-0.08	0.03	0.42	-0.03	0.28	0.47	1.00			
26	English-Future Performance	0.04	0.08	0.05	-0.01	0.10	0.01	-0.05	0.12	0.03	-0.03	-0.01	1.00		
27	Mathematics-Future Performance	-0.04	-0.13	-0.14	0.48	0.02	-0.09	0.12	0.01	0.13	0.13	0.27	0.11	1.00	
28	Science-Future Performance	0.05	0.04	-0.03	0.20	0.04	0.05	0.09	0.08	0.19	0.16	0.17	0.22	0.36	1.00
29	Mathematics-Advanced Coursework	0.01	0.10	0.14	-0.31	-0.02	0.05	-0.07	-0.04	-0.09	-0.06	-0.19	-0.06	-0.35	-0.11
30	Science-Advanced Coursework	-0.08	-0.06	0.02	-0.09	-0.08	-0.06	0.00	-0.13	-0.15	-0.08	-0.10	-0.08	-0.08	-0.28
31	Engineering-Advanced Coursework	0.03	0.14	0.19	-0.26	0.08	0.04	-0.28	0.03	-0.13	-0.22	-0.42	-0.02	-0.17	-0.13
32	STEM Major/Non-STEM Major	0.02	0.02	-0.01	0.20	0.08	0.01	0.06	0.07	0.12	0.11	0.22	-0.01	0.18	0.15
33	Known Adults-Scientists	-0.08	-0.05	0.01	-0.05	-0.06	-0.06	0.03	-0.07	-0.09	-0.06	-0.04	-0.06	-0.04	-0.08
34	Known Adults-Engineers	-0.02	0.04	0.04	-0.14	-0.03	0.01	-0.03	-0.06	-0.10	-0.09	-0.17	-0.05	-0.11	-0.08
35	Known Adults-Mathematicians	-0.03	-0.01	-0.03	-0.10	-0.03	-0.02	-0.01	-0.04	-0.04	-0.03	-0.01	-0.04	-0.02	-0.01
36	Known Adults-Technologists	0.00	0.01	0.01	-0.09	-0.05	-0.02	-0.11	-0.05	-0.06	-0.06	-0.06	-0.01	-0.03	-0.05
37	Rural/Urban Status	0.01	-0.03	-0.06	0.03	0.00	-0.02	0.08	0.02	0.02	0.05	0.07	-0.03	0.03	0.00
38	Title I School Status	-0.02	0.02	0.05	-0.03	0.03	0.03	0.02	0.01	0.00	-0.05	-0.08	0.01	-0.05	-0.07

Var #	Variable	29	30	31	32	33	34	35	36	37	38
1	Math Attitudes										
2	Science Attitudes										
3	Engineering Attitudes										
4	21st Century Skills										
5	STEM Self-Efficacy Composite										
6	Dosage										
7	Outreach Program										
8	Pre-/Post										
9	Grade Level										
10	School Type										
11	Gender										
12	Over/Under-represented in STEM										
13	Race/Ethnicity										
14	Physics Career Interest										
15	Environmental Career Interest										
16	Biology Career Interest										
17	Veterinary Career Interest										
18	Mathematics Career Interest										
19	Medical Career Interest										
20	Earth Science Career Interest										
21	Computer Science Career Interest										
22	Medical Science Career Interest										
23	Chemistry Career Interest										
24	Energy Career Interest										
25	Engineering Career Interest										
26	English-Future Performance										
27	Mathematics-Future Performance										
28	Science-Future Performance										
29	Mathematics-Advanced Coursework	1.00									
30	Science-Advanced Coursework	0.42	1.00								
31	Engineering-Advanced Coursework	0.36	0.37	1.00							
32	STEM Major/Non-STEM Major	-0.18	-0.17	-0.17	1.00						
33	Known Adults-Scientists	0.05	0.07	0.05	-0.03	1.00					
34	Known Adults-Engineers	0.09	0.10	0.14	-0.08	0.19	1.00				
35	Known Adults-Mathematicians	0.02	0.03	0.01	0.03	0.23	0.19	1.00			
36	Known Adults-Technologists	0.03	0.02	0.06	0.00	0.23	0.22	0.28	1.00		
37	Rural/Urban Status	-0.04	0.00	-0.04	0.06	-0.05	-0.01	0.01	-0.01	1.00	
38	Title I School Status	0.04	0.08	0.03	-0.08	0.07	0.07	0.01	-0.01	-0.16	1.00

Appendix C

Collinearity Diagnostics

Using the standard employed by Adelman (2006), tolerance values less than .5 were examined for collinearity by calculating the variance inflation factors (VIF) of these variables. While there is no formal measure that conclusively identifies collinearity, VIFs larger than 5 are typically considered problematic. Using that standard, these variables were removed before the multilevel analysis was performed.

Model I: Demographic Variables

Variable	VIF	SQRT VIF	R-Tolerance	Squared
STEM_SE	2.29e+13	4.8e+06	0.0000	1.0000
Gender	1.19	1.09	0.8379	0.1621
GrpRace	1.12	1.06	0.8950	0.1050
PrePost	1.02	1.01	0.9835	0.0165
Grade	1.07	1.04	0.9313	0.0687
DosageGrp	1.07	1.04	0.9334	0.0666
Math Attitude	4.61e+12	2.1e+06	0.0000	1.0000
Science Attitudes	3.90e+12	2.0e+06	0.0000	1.0000
EngTech Attitudes	4.36e+12	2.1e+06	0.0000	1.0000
21stCenturySkills	1.46	1.21	0.6858	0.3142

Mean VIF 3.58e+12

	Eigenval	Cond Index
1	9.9942	1.0000
2	0.6155	4.0297
3	0.1149	9.3252
4	0.1006	9.9696
5	0.0792	11.2306
6	0.0454	14.8400
7	0.0179	23.6273
8	0.0157	25.2548
9	0.0104	31.0048
10	0.0062	40.0129
11	-0.0000	.

Condition Number .
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0000

Collinearity Diagnostics--with collinear factors removed

Variable	VIF	SQRT VIF	R-Tolerance	Squared
STEM_SE	1.53	1.24	0.6526	0.3474
Gender	1.11	1.05	0.8988	0.1012
GrpRace	1.12	1.06	0.8958	0.1042
PrePost	1.02	1.01	0.9847	0.0153
Grade	1.06	1.03	0.9454	0.0546
DosageGrp	1.07	1.03	0.9337	0.0663
21stCenturySkills	1.45	1.20	0.6902	0.3098

Mean VIF 1.19

	Eigenval	Cond Index
1	7.0880	1.0000
2	0.5933	3.4564
3	0.1080	8.1011
4	0.0899	8.8814
5	0.0750	9.7186
6	0.0328	14.6932
7	0.0067	32.4782
8	0.0063	33.5612

Condition Number 33.5612
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.5715

Appendix D

Stata Multilevel Model Results

Multilevel Model Results

Model I:

```
Mixed-effects GLM                          Number of obs     =      7524
Family:              Gaussian
Link:                identity
Group variable:        Program             Number of groups  =        25

                                           Obs per group: min =         1
                                                          avg =     301.0
                                                          max =      4172

Integration method: mcaghermite              Integration points =        7

                                           Wald chi2(3)      =    288.32
Log likelihood = -5420.6501                Prob > chi2       =    0.0000
------------------------------------------------------------------------------
     STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
      Gender |  -.1562205   .0119824   -13.04   0.000    -.1797057   -.1327354
     GrpRace |  -.1348842   .0134919   -10.00   0.000    -.1613279   -.1084404
     PrePost |   .0483755   .0123044     3.93   0.000     .0242592    .0724918
       _cons |   4.204651   .0562894    74.70   0.000     4.094326    4.314976
--------------+---------------------------------------------------------------
Program       |
   var(_cons)|   .0537939   .0170543                      .0288987    .1001357
--------------+---------------------------------------------------------------
var(e.STEM_SE)|   .2450324   .0040012                      .2373143    .2530014
------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =   947.37 Prob>=chibar2 = 0.0000


Mixed-effects GLM                          Number of obs     =      7490
Family:              Gaussian
Link:                identity
Group variable:        Program             Number of groups  =        25

                                           Obs per group: min =         1
                                                          avg =     299.6
```

```
                                                  max =      4171

Integration method: mcaghermite                 Integration points =        7

                                                Wald chi2(4)       =    306.51
Log likelihood = -5384.4216                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
     STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
      Gender |   -.154965   .0119926   -12.92   0.000    -.1784702   -.1314599
     GrpRace |  -.1258933   .0136089    -9.25   0.000    -.1525662   -.0992204
     PrePost |   .0503208   .0123041     4.09   0.000     .0262052    .0744365
       Grade |   .0151033   .0032791     4.61   0.000     .0086764    .0215301
       _cons |   4.064167   .0644778    63.03   0.000     3.937793    4.190541
--------------+---------------------------------------------------------------
Program       |
   var(_cons)|   .0548941   .0174156                      .0294764    .1022297
--------------+---------------------------------------------------------------
var(e.STEM_SE)|    .244244   .0039974                      .2365334    .2522058
------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =   883.17 Prob>=chibar2 = 0.0000


Mixed-effects GLM                               Number of obs      =      7490
Family:              Gaussian
Link:                identity
Group variable:        Program                  Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     299.6
                                                               max =      4171

Integration method: mcaghermite                 Integration points =        7

                                                Wald chi2(5)       =    377.60
Log likelihood = -5350.4232                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
     STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
      Gender |  -.1554212   .0119382   -13.02   0.000    -.1788196   -.1320227
     GrpRace |  -.1333449   .0135769    -9.82   0.000    -.1599551   -.1067348
     PrePost |   .0404982   .0123059     3.29   0.001     .0163789    .0646174
       Grade |   .0184831   .0032902     5.62   0.000     .0120344    .0249318
  DosageCount |   .0349314   .0042266     8.26   0.000     .0266475    .0432154
       _cons |   3.983958   .0652155    61.09   0.000     3.856137    4.111778
--------------+---------------------------------------------------------------
```

```
Program       |
   var(_cons)|   .0553228   .0175432                    .0297155    .1029973
--------------+-----------------------------------------------------------------
var(e.STEM_SE)|   .2420248   .0039611                    .2343844    .2499144
------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =   864.73 Prob>=chibar2 = 0.0000



Mixed-effects GLM                               Number of obs     =      7458
Family:              Gaussian
Link:                identity
Group variable:        Program                  Number of groups  =        25

                                                Obs per group: min =         1
                                                               avg =     298.3
                                                               max =      4164

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(6)      =   3572.81
Log likelihood = -4042.3233                     Prob > chi2       =    0.0000
------------------------------------------------------------------------------
                STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                 Gender |  -.2209518   .0101441   -21.78   0.000    -.2408338   -.2010697
                GrpRace |  -.1265441   .0114544   -11.05   0.000    -.1489944   -.1040939
                PrePost |   .0220928   .0103771     2.13   0.033      .001754    .0424315
                  Grade |   .0077336   .0027782     2.78   0.005     .0022884    .0131788
            DosageCount |   .0223241   .0035732     6.25   0.000     .0153207    .0293275
stCenturySkillsAttitudeswei |   .5281646   .0095793    55.14   0.000     .5093895    .5469397
                  _cons |    1.94766    .064997    29.97   0.000     1.820268    2.075052
----------------------------+-------------------------------------------------------------
Program                     |
              var(_cons)|   .0354564   .0114663                    .0188115    .0668291
----------------------------+-------------------------------------------------------------
           var(e.STEM_SE)|   .1715108   .0028132                    .1660848    .1771142
------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =   846.14 Prob>=chibar2 = 0.0000

Mixed-effects GLM                               Number of obs     =      7367
Family:              Gaussian
Link:                identity
Group variable:        Program                  Number of groups  =        25

                                                Obs per group: min =         1
```

```
                                                avg =     294.7
                                                max =      4138

Integration method: mcaghermite                 Integration points =        7

                                          Wald chi2(18)      =  10157.38
Log likelihood = -2233.0678                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
                STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                 Gender |  -.0587305   .0090152    -6.51   0.000    -.0763999   -.0410611
                GrpRace |  -.0759195   .0091217    -8.32   0.000    -.0937977   -.0580413
                PrePost |   .0275789   .0082236     3.35   0.001     .0114609    .0436969
                  Grade |   .0011854   .0022979     0.52   0.606    -.0033184    .0056892
            DosageCount |   .0160959   .0028347     5.68   0.000     .0105401    .0216517
stCenturySkillsAttitudeswei |   .3860997   .0080124    48.19   0.000     .3703957    .4018038
             MHFuture_1 |   .0754117   .0056167    13.43   0.000     .0644032    .0864203
             MHFuture_2 |  -.0043676   .0056712    -0.77   0.441    -.0154829    .0067477
             MHFuture_3 |   .0406851   .0055665     7.31   0.000      .029775    .0515952
             MHFuture_4 |  -.0375998   .0053286    -7.06   0.000    -.0480436    -.027156
             MHFuture_5 |   .1361972   .0049287    27.63   0.000     .1265372    .1458572
             MHFuture_6 |  -.0161951   .0063127    -2.57   0.010    -.0285678   -.0038225
             MHFuture_7 |  -.0265996   .0054572    -4.87   0.000    -.0372955   -.0159037
             MHFuture_8 |   .0194872   .0045896     4.25   0.000     .0104918    .0284825
             MHFuture_9 |   .0287605   .0063945     4.50   0.000     .0162275    .0412936
            MHFuture_10 |   .0478066   .0053827     8.88   0.000     .0372567    .0583564
            MHFuture_11 |   .0092167   .0057659     1.60   0.110    -.0020843    .0205178
            MHFuture_12 |   .1582923   .0059264    26.71   0.000     .1466769    .1699077
                  _cons |   1.176078   .0490615    23.97   0.000     1.079919    1.272236
----------------------------+-------------------------------------------------------------
Program                     |
              var(_cons)|   .0060849   .0022096                      .0029865     .012398
----------------------------+-------------------------------------------------------------
           var(e.STEM_SE)|   .1067236   .0017609                      .1033274    .1102313
------------------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =   121.40 Prob>=chibar2 = 0.0000

Mixed-effects GLM                               Number of obs      =      7345
Family:              Gaussian
Link:                identity
Group variable:        Program                  Number of groups   =        25

                                          Obs per group: min =         1
                                                avg =     293.8
                                                max =      4131
```

```
Integration method: mcaghermite              Integration points =       7

                                          Wald chi2(21)      =  13184.96
Log likelihood = -1644.8682                  Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
                STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                 Gender |  -.0417271   .0083938    -4.97   0.000    -.0581786   -.0252757
                GrpRace |  -.0512911   .0084342    -6.08   0.000    -.0678217   -.0347604
                PrePost |   .0246152   .0075965     3.24   0.001     .0097264     .039504
                  Grade |  -.0007003   .0021158    -0.33   0.741    -.0048473    .0034467
             DosageCount |   .0127364   .0026229     4.86   0.000     .0075956    .0178773
stCenturySkillsAttitudeswei |   .3197823   .0078855    40.55   0.000      .304327    .3352376
             MHFuture_1 |   .0657869   .0052133    12.62   0.000      .055569    .0760047
             MHFuture_2 |  -.0061942   .0052489    -1.18   0.238    -.0164819    .0040935
             MHFuture_3 |   .0341318   .0051646     6.61   0.000     .0240094    .0442542
             MHFuture_4 |  -.0277258   .0049319    -5.62   0.000    -.0373923   -.0180594
             MHFuture_5 |   .0924504    .004958    18.65   0.000      .082733    .1021678
             MHFuture_6 |  -.0201633   .0058439    -3.45   0.001    -.0316171   -.0087096
             MHFuture_7 |  -.0175022   .0050665    -3.45   0.001    -.0274324    -.007572
             MHFuture_8 |   .0243281   .0042514     5.72   0.000     .0159955    .0326607
             MHFuture_9 |   .0309214    .005923     5.22   0.000     .0193125    .0425304
            MHFuture_10 |   .0364543   .0050033     7.29   0.000     .0266481    .0462604
            MHFuture_11 |   .0159743   .0053452     2.99   0.003     .0054978    .0264507
            MHFuture_12 |   .1531995   .0054855    27.93   0.000     .1424481    .1639508
              MHClass_1 |  -.0021751   .0075281    -0.29   0.773      -.01693    .0125798
              MHClass_2 |   .2003701   .0086659    23.12   0.000     .1833852     .217355
              MHClass_3 |    .187771   .0093227    20.14   0.000     .1694988    .2060431
                  _cons |   .5498965   .0479826    11.46   0.000     .4558523    .6439407
----------------------------+-------------------------------------------------------------
Program                     |
              var(_cons)|   .0031888   .0013154                      .0014207    .0071575
----------------------------+-------------------------------------------------------------
            var(e.STEM_SE)|    .091195    .001507                      .0882887    .0941971
------------------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =    56.32 Prob>=chibar2 = 0.0000


Mixed-effects GLM                              Number of obs      =      7241
Family:              Gaussian
Link:                identity
Group variable:        Program                 Number of groups   =        25
```

```
                                                Obs per group: min =         1
                                                           avg =     289.6
                                                           max =      4089

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(25)      =  12922.96
Log likelihood = -1602.7903                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
                STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                 Gender |  -.0407844   .0084445    -4.83   0.000    -.0573354   -.0242335
                GrpRace |  -.0501134   .0084941    -5.90   0.000    -.0667615   -.0334652
                PrePost |    .023902   .0076265     3.13   0.002     .0089544    .0388496
                  Grade |  -.0009767   .0021409    -0.46   0.648    -.0051727    .0032193
             DosageCount |   .0127119     .00263     4.83   0.000     .0075572    .0178665
stCenturySkillsAttitudeswei |   .3169489   .0079539    39.85   0.000     .3013595    .3325383
             MHFuture_1 |   .0654572   .0052433    12.48   0.000     .0551806    .0757338
             MHFuture_2 |   -.005347   .0052835    -1.01   0.312    -.0157025    .0050084
             MHFuture_3 |   .0340065   .0051984     6.54   0.000     .0238177    .0441952
             MHFuture_4 |  -.0279943   .0049674    -5.64   0.000    -.0377301   -.0182584
             MHFuture_5 |   .0934657   .0049968    18.71   0.000     .0836721    .1032593
             MHFuture_6 |  -.0199892   .0058879    -3.39   0.001    -.0315292   -.0084492
             MHFuture_7 |  -.0180452   .0050992    -3.54   0.000    -.0280394   -.0080511
             MHFuture_8 |   .0260205   .0042871     6.07   0.000      .017618    .0344231
             MHFuture_9 |   .0308267   .0059725     5.16   0.000     .0191209    .0425326
            MHFuture_10 |   .0352055   .0050274     7.00   0.000      .025352     .045059
            MHFuture_11 |   .0162147   .0053709     3.02   0.003      .005688    .0267414
            MHFuture_12 |   .1508131   .0055312    27.27   0.000     .1399721    .1616541
              MHClass_1 |  -.0010801   .0075677    -0.14   0.887    -.0159125    .0137523
              MHClass_2 |   .1994565   .0087177    22.88   0.000     .1823701    .2165428
              MHClass_3 |    .186546   .0093992    19.85   0.000     .1681238    .2049682
               Adults_1 |  -.0151436   .0048512    -3.12   0.002    -.0246519   -.0056353
               Adults_2 |  -.0116258   .0054753    -2.12   0.034    -.0223571   -.0008944
               Adults_3 |   .0102286   .0049061     2.08   0.037     .0006128    .0198443
               Adults_4 |  -.0033818   .0045614    -0.74   0.458    -.0123221    .0055585
                  _cons |   .5988669   .0520001    11.52   0.000     .4969485    .7007853
----------------------------+-------------------------------------------------------------
Program                     |
             var(_cons)|   .0032157    .001317                      .001441    .0071759
----------------------------+-------------------------------------------------------------
           var(e.STEM_SE)|   .0907175   .0015098                      .087806    .0937256
------------------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =    55.53 Prob>=chibar2 = 0.0000
```

Model II:

```
Mixed-effects logistic regression               Number of obs      =      7629
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     305.2
                                                               max =      4206

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(0)       =         .
Log likelihood =  -3239.971                     Prob > chi2        =         .
------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
           _cons |   1.454532   .1941491     7.49   0.000     1.074006    1.835057
-------------------+----------------------------------------------------------------
Program            |
        var(_cons)|   .7300906   .2822173                      .3422504    1.557434
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   415.60 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7622
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     304.9
                                                               max =      4203

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(1)       =     43.20
Log likelihood = -3216.0792                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |  -.4272232   .0649995    -6.57   0.000    -.5546199   -.2998264
           _cons |    2.10285   .2243005     9.38   0.000     1.663229    2.542471
-------------------+----------------------------------------------------------------
Program            |
        var(_cons)|   .7864119   .3007468                      .3716429     1.66408
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   400.83 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7598
Group variable:         Program                 Number of groups   =        25
```

```
                                                Obs per group: min =         1
                                                           avg =     303.9
                                                           max =      4191

Integration method: mcaghermite                 Integration points =        7

                                                Wald chi2(8)      =    117.59
Log likelihood = -3166.4929                     Prob > chi2       =    0.0000
------------------------------------------------------------------------------
  Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
            Gender |      -.434186   .0655786    -6.62   0.000    -.5627178   -.3056543
                   |Race |
         2. Asian  |    1.12627   .2074924     5.43   0.000     .7195924    1.532948
         3. Black  |      .4792515   .1802085     2.66   0.008     .1260493    .8324537
 4. Pacific Islander  |  -.3998275   .4878093    -0.82   0.412    -1.355916    .5562611
         5. White  |      .9777415   .1733748     5.64   0.000      .637933     1.31755
  6. Hispanic/Latino  |   .4382913   .2274391     1.93   0.054    -.0074811    .8840636
     7. Multiracial  |   .7198837   .2161506 3.33   0.001     .2962363    1.143531
         8. Other  |      1.072848   .2898384     3.70   0.000     .5047748     1.64092
                   |
            _cons |   1.357644     .28179     4.82   0.000     .8053462    1.909943
---------------------+--------------------------------------------------------------
Program              |
         var(_cons)|   .8128622    .309189                      .3856957    1.713125
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   351.89 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs     =      7622
Group variable:         Program                 Number of groups  =        25

                                                Obs per group: min =         1
                                                           avg =     304.9
                                                           max =      4203

Integration method: mcaghermite                 Integration points =        7

                                                Wald chi2(1)      =     43.20
Log likelihood = -3216.0792                     Prob > chi2       =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
         Gender |   .6523179   .0424004    -6.57   0.000     .5742905    .7409468
          _cons |   8.189476   1.836903     9.38   0.000     5.276321    12.71104
--------------------+---------------------------------------------------------------
```

```
Program          |
      var(_cons)|   .7864119   .3007468                  .3716429     1.66408
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   400.83 Prob>=chibar2 = 0.0000

 Mixed-effects logistic regression              Number of obs      =      7598
Group variable:        Program                Number of groups   =        25

                                              Obs per group: min =         1
                                                             avg =     303.9
                                                             max =      4191

Integration method: mcaghermite                Integration points =         7

                                              Wald chi2(2)       =     93.28
Log likelihood = -3177.7799                   Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |   -.434773   .0653572    -6.65   0.000    -.5628707   -.3066753
         GrpRace |  -.5208454   .0742215    -7.02   0.000    -.6663168    -.375374
           _cons |   2.363685   .2299474    10.28   0.000     1.912997    2.814374
-------------------+----------------------------------------------------------------
Program          |
      var(_cons)|   .8067207   .3065022                  .3831079    1.698733
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   349.64 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression              Number of obs      =      7598
Group variable:        Program                Number of groups   =        25

                                              Obs per group: min =         1
                                                             avg =     303.9
                                                             max =      4191

Integration method: mcaghermite                Integration points =         7

                                              Wald chi2(2)       =     93.28
Log likelihood = -3177.7799                   Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |   .6474116    .042313    -6.65   0.000     .5695716    .7358895
         GrpRace |   .5940182   .0440889    -7.02   0.000     .5135968    .6870323
           _cons |   10.63005   2.444354    10.28   0.000     6.773355    16.68273
-------------------+----------------------------------------------------------------
```

```
Program          |
      var(_cons)|   .8067207   .3065022                    .3831079    1.698733
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   349.64 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression              Number of obs      =      7594
Group variable:        Program                 Number of groups   =        25

                                               Obs per group: min =         1
                                                              avg =     303.8
                                                              max =      4191

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(3)       =     93.93
Log likelihood = -3174.0776                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |  -.4338015   .0654049    -6.63   0.000    -.5619927   -.3056103
        GrpRace |  -.5257054   .0742881    -7.08   0.000    -.6713073   -.3801034
        PrePost |  -.0015107   .0705694    -0.02   0.983    -.1398243    .1368029
          _cons |   2.367213   .2523757     9.38   0.000     1.872566    2.861861
-------------------+----------------------------------------------------------------
Program          |
      var(_cons)|   .8070423   .3068975                    .3830065    1.700538
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   342.36 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression              Number of obs      =      7553
Group variable:        Program                 Number of groups   =        25

                                               Obs per group: min =         1
                                                              avg =     302.1
                                                              max =      4190

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(4)       =    157.52
Log likelihood = -3111.7351                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |  -.4328272   .0658927    -6.57   0.000    -.5619745   -.3036798
        GrpRace |  -.4618636   .0750344    -6.16   0.000    -.6089284   -.3147988
        PrePost |   .0160279   .0710286     0.23   0.821    -.1231856    .1552415
```

```
          Grade |   .1595465   .0194776     8.19   0.000     .1213712    .1977219
          _cons |   .9170248   .2911539     3.15   0.002     .3463736    1.487676
-------------------+----------------------------------------------------------------
Program            |
       var(_cons)|    .577631   .2267872                      .2675809    1.246941
------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   233.75 Prob>=chibar2 = 0.0000


Mixed-effects logistic regression               Number of obs      =      7553
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     302.1
                                                               max =      4190

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(5)       =    163.89
Log likelihood = -3108.5126                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------
Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |  -.4311732   .0659755    -6.54   0.000    -.5604828   -.3018637
        GrpRace |   -.473325   .0751344    -6.30   0.000    -.6205857   -.3260642
        PrePost |   .0138141   .0710905     0.19   0.846    -.1255207    .1531488
          Grade |   .1628722   .0194963     8.35   0.000     .1246601    .2010843
      DosageGrp |   .2431422   .0977797     2.49   0.013     .0514976    .4347869
          _cons |   .6362715    .311941     2.04   0.041     .0248783    1.247665
-------------------+----------------------------------------------------------------
Program            |
       var(_cons)|   .5801877   .2276214                      .2689193    1.251743
------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   236.65 Prob>=chibar2 = 0.0000

.
. melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp || Program:,
intmethod(mcaghermite) or

Fitting fixed-effects model:

Iteration 0:   log likelihood =  -3247.661
Iteration 1:   log likelihood = -3226.9569
Iteration 2:   log likelihood = -3226.8364
Iteration 3:   log likelihood = -3226.8364
```

```
Refining starting values:

Grid node 0:   log likelihood = -3114.9504

Fitting full model:

Iteration 0:   log likelihood = -3114.9504  (not concave)
Iteration 1:   log likelihood = -3110.4516
Iteration 2:   log likelihood = -3109.2987
Iteration 3:   log likelihood = -3108.5189
Iteration 4:   log likelihood = -3108.5127
Iteration 5:   log likelihood = -3108.5126

Mixed-effects logistic regression               Number of obs      =      7553
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     302.1
                                                               max =      4190

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(5)       =    163.89
Log likelihood = -3108.5126                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          Gender |   .6497464   .0428673    -6.54   0.000     .5709334    .7394389
         GrpRace |   .6229276   .0468033    -6.30   0.000     .5376294    .7217588
         PrePost |    1.01391   .0720793     0.19   0.846     .8820375    1.165498
           Grade |   1.176886   .0229449     8.35   0.000     1.132763    1.222728
       DosageGrp |    1.27525   .1246935     2.49   0.013     1.052847    1.544634
           _cons |   1.889423   .5893885     2.04   0.041      1.02519    3.482201
-------------------+----------------------------------------------------------------
Program            |
       var(_cons)|   .5801877   .2276214                      .2689193    1.251743
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   236.65 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7545
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     301.8
                                                               max =      4187
```

```
Integration method: mcaghermite              Integration points =        7

                                          Wald chi2(6)       =    486.10
Log likelihood = -2925.8191                  Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
     Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
                 Gender |  -.3161755   .0685875    -4.61   0.000    -.4506046   -.1817464
                GrpRace |  -.3571985    .077568    -4.60   0.000     -.509229   -.2051681
                PrePost |  -.0153484   .0734045    -0.21   0.834    -.1592185    .1285218
                  Grade |    .158293   .0201571     7.85   0.000     .1187858    .1978003
              DosageGrp |   .1470413   .1007272     1.46   0.144    -.0503805     .344463
MathAtttitudesweightedAvg |   .8041877   .0435303    18.47   0.000     .7188699    .8895056
                 _cons |   -2.51003   .3516519    -7.14   0.000    -3.199255   -1.820805
--------------------------+---------------------------------------------------------------
Program                   |
             var(_cons)|   .4296326   .1780407                      .190703    .9679145
------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   121.41 Prob>=chibar2 = 0.0000
Mixed-effects logistic regression               Number of obs      =      7531
Group variable:         Program                 Number of groups   =        25

                                          Obs per group: min =         1
                                                         avg =     301.2
                                                         max =      4179

Integration method: mcaghermite              Integration points =        7

                                          Wald chi2(6)       =    553.17
Log likelihood = -2863.2445                  Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
       Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                  Gender |  -.4152895   .0689678    -6.02   0.000     -.550464   -.2801151
                 GrpRace |  -.3582346   .0788761    -4.54   0.000     -.512829   -.2036402
                 PrePost |  -.0666258   .0741658    -0.90   0.369    -.2119881    .0787366
                   Grade |   .1374623   .0201513     6.82   0.000     .0979664    .1769581
               DosageGrp |   .0595066   .1044225     0.57   0.569    -.1451577    .2641709
ScienceAttitudesweightedAvg |    1.02357   .0505511    20.25   0.000      .924492    1.122649
                  _cons |  -3.064949    .350589    -8.74   0.000    -3.752091   -2.377808
----------------------------+-------------------------------------------------------------
Program                   |
             var(_cons)|   .3366885   .1489753                      .1414475    .8014222
------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   118.56 Prob>=chibar2 = 0.0000
```

```
Mixed-effects logistic regression              Number of obs     =      7498
Group variable:        Program                 Number of groups  =        25

                                               Obs per group: min =         1
                                                              avg =     299.9
                                                              max =      4174

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(6)      =    305.61
Log likelihood = -2980.3704                    Prob > chi2       =    0.0000
------------------------------------------------------------------------------------------
       Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                   Gender |  -.2004513   .0702133    -2.85   0.004    -.3380667   -.0628358
                  GrpRace |  -.4483081    .076949    -5.83   0.000    -.5991255   -.2974908
                  PrePost |   .0178553   .0726679     0.25   0.806    -.1245711    .1602818
                    Grade |   .1790278    .019998     8.95   0.000     .1398324    .2182232
                 DosageGrp |   .1967172    .101814     1.93   0.053    -.0028346     .396269
EngTechAttitudesweightedAvg |   .5944422   .0499023    11.91   0.000     .4966355     .692249
                    _cons |  -2.023545   .3842191    -5.27   0.000    -2.776601   -1.270489
----------------------------+-------------------------------------------------------------
Program                     |
                 var(_cons)|   .5620271   .2261231                      .2554401    1.236589
------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   132.76 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression              Number of obs     =      7476
Group variable:        Program                 Number of groups  =        25

                                               Obs per group: min =         1
                                                              avg =     299.0
                                                              max =      4166

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(6)      =    212.37
Log likelihood = -3017.8704                    Prob > chi2       =    0.0000
------------------------------------------------------------------------------------------
       Major_STEM_nonSTEM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                   Gender |  -.4907014   .0677086    -7.25   0.000    -.6234079   -.3579949
                  GrpRace |  -.4984657   .0761319    -6.55   0.000    -.6476815     -.34925
                  PrePost |   .0057891   .0720886     0.08   0.936     -.135502    .1470802
                    Grade |   .1643961   .0198081     8.30   0.000     .1255729    .2032193
                 DosageGrp |   .2022989   .0994797     2.03   0.042     .0073222    .3972755
```

```
stCenturySkillsAttitudeswei |   .4008631   .0618771     6.48   0.000     .2795862      .52214
                  _cons |  -.9227899   .3878858    -2.38   0.017    -1.683032   -.1625477
----------------------------+----------------------------------------------------------------
Program                     |
              var(_cons)|   .5101239   .2043529                      .2326425    1.118568
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   184.59 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7469
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     298.8
                                                               max =      4164

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(8)       =    691.16
Log likelihood = -2719.5753                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------------
        Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------------
                    Gender |   .7688911   .0556526    -3.63   0.000     .6671977    .8860845
                   GrpRace |   .7546553   .0609946    -3.48   0.000     .6440961     .884192
                   PrePost |   .9315555   .0708989    -0.93   0.352     .8024637    1.081414
                     Grade |   1.160208   .0240559     7.17   0.000     1.114004    1.208328
                 DosageGrp |   1.032215   .1098972     0.30   0.766     .8378088    1.271731
  MathAtttitudesweightedAvg |   1.959551   .0958803    13.75   0.000     1.780359    2.156779
ScienceAttitudesweightedAvg |   2.655329   .1505118    17.23   0.000     2.376128    2.967338
stCenturySkillsAttitudeswei |    .658365   .0493889    -5.57   0.000     .5683446    .7626438
                  _cons |   .0184847   .0076747    -9.61   0.000     .0081923    .0417083
----------------------------+----------------------------------------------------------------
Program                     |
              var(_cons)|   .2741472   .1293459                      .1087369    .6911794
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    62.85 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7458
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     298.3
                                                               max =      4164

Integration method: mcaghermite                 Integration points =         7
```

```
                                                  Wald chi2(9)      =    691.63
Log likelihood = -2710.4822                       Prob > chi2       =    0.0000
------------------------------------------------------------------------------------------------
        Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------------
                    Gender |    .82421   .0628912    -2.53   0.011     .7097201     .957169
                   GrpRace |   .7577033   .0614047    -3.42   0.001     .6464237    .8881392
                   PrePost |   .9347676   .0713284    -0.88   0.377     .8049183    1.085564
                     Grade |   1.165479    .024316     7.34   0.000     1.118782    1.214125
                 DosageGrp |    1.04156   .1121443     0.38   0.705     .8434039    1.286272
  MathAtttitudesweightedAvg |   1.919348   .0952914    13.13   0.000      1.74138    2.115505
ScienceAttitudesweightedAvg |   2.542956   .1486364    15.97   0.000     2.267702    2.851621
EngTechAttitudesweightedAvg |   1.182787   .0717372     2.77   0.006      1.05022    1.332087
stCenturySkillsAttitudeswei |   .6239319   .0484261    -6.08   0.000     .5358852    .7264449
                      _cons |   .0136858   .0059037    -9.95   0.000      .005876    .0318756
----------------------------+-------------------------------------------------------------------
Program                     |
                 var(_cons)|   .2889432   .1365083                      .1144645    .7293804
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    53.76 Prob>=chibar2 = 0.0000


Mixed-effects logistic regression               Number of obs      =      7367
Group variable:         Program                 Number of groups   =        25

                                                  Obs per group: min =         1
                                                                 avg =     294.7
                                                                 max =      4138

Integration method: mcaghermite                 Integration points =         7

                                                  Wald chi2(21)     =    737.42
Log likelihood = -2619.0636                       Prob > chi2       =    0.0000
------------------------------------------------------------------------------------------------
        Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------------
                    Gender |   .7820587   .0647791    -2.97   0.003     .6648644    .9199107
                   GrpRace |   .7154117   .0595187    -4.03   0.000     .6077715    .8421156
                   PrePost |   .9452608   .0735889    -0.72   0.470      .811494    1.101078
                     Grade |   1.175589   .0261155     7.28   0.000     1.125502    1.227905
                 DosageGrp |   1.059947   .1165103     0.53   0.596     .8545144    1.314768
  MathAtttitudesweightedAvg |   1.720409     .10829     8.62   0.000     1.520734    1.946301
ScienceAttitudesweightedAvg |   2.340839   .1520553    13.09   0.000     2.061007    2.658664
EngTechAttitudesweightedAvg |   .9999141   .0798323    -0.00   0.999     .8550736    1.169289
stCenturySkillsAttitudeswei |   .6048722   .0491323    -6.19   0.000      .515849    .7092586
                  MHFuture_1 |   1.028476   .0540747     0.53   0.593     .9277695    1.140114
```

```
          MHFuture_2 |   .9702061   .0516323    -0.57   0.570     .8741076     1.07687
          MHFuture_3 |   1.071587   .0555462     1.33   0.182     .9680658    1.186177
          MHFuture_4 |   1.048334   .0509023     0.97   0.331     .9531677    1.153002
          MHFuture_5 |   1.142059   .0600961     2.52   0.012     1.030143    1.266133
          MHFuture_6 |   1.267737   .0730038     4.12   0.000     1.132432    1.419209
          MHFuture_7 |   .9080046   .0468023    -1.87   0.061     .8207551    1.004529
          MHFuture_8 |   .9803522   .0429137    -0.45   0.650      .89975    1.068175
          MHFuture_9 |   1.053294   .0621492     0.88   0.379     .9382637    1.182427
         MHFuture_10 |   .9965435   .0503564    -0.07   0.945     .9025767    1.100293
         MHFuture_11 |   .9724497   .0530509    -0.51   0.609     .8738378     1.08219
         MHFuture_12 |   1.290543   .0746592     4.41   0.000     1.152205    1.445491
               _cons |   .0110501   .0051462    -9.67   0.000     .0044356    .0275286
----------------------------+----------------------------------------------------------------
Program                     |
            var(_cons)|   .2648848   .1315336                      .1000868    .7010314
------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    40.06 Prob>=chibar2 = 0.0000



Mixed-effects logistic regression              Number of obs      =      7345
Group variable:         Program                Number of groups   =        25

                                               Obs per group: min =         1
                                                              avg =     293.8
                                                              max =      4131

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(24)      =    744.13
Log likelihood = -2599.8945                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
       Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                   Gender |   .7861087   .0658289    -2.87   0.004     .6671182    .9263228
                  GrpRace |   .7172809   .0599079    -3.98   0.000     .6089704    .8448554
                  PrePost |    .936205   .0731817    -0.84   0.399     .8032188    1.091209
                    Grade |   1.179452   .0263197     7.40   0.000     1.128978    1.232182
                 DosageGrp |   1.053976   .1166482     0.47   0.635     .8484461    1.309293
  MathAtttitudesweightedAvg |   1.764679   .1337779     7.49   0.000     1.521028    2.047359
ScienceAttitudesweightedAvg |   2.557314   .1834782    13.09   0.000     2.221843    2.943437
EngTechAttitudesweightedAvg |   .9939745   .0797401    -0.08   0.940     .8493543    1.163219
stCenturySkillsAttitudeswei |   .6372092   .0533336    -5.38   0.000      .540801     .750804
          MHFuture_1 |   1.037017   .0547775     0.69   0.491     .9350258    1.150133
          MHFuture_2 |   .9683656    .051798    -0.60   0.548     .8719839      1.0754
```

```
          MHFuture_3 |   1.081144   .0563319     1.50   0.134     .9761862    1.197387
          MHFuture_4 |   1.051705   .0512892     1.03   0.301     .9558344    1.157191
          MHFuture_5 |   1.136719   .0604737     2.41   0.016     1.024163    1.261645
          MHFuture_6 |   1.265683   .0731768     4.08   0.000     1.130087    1.417549
          MHFuture_7 |   .9052974   .0469296    -1.92   0.055     .8178354    1.002113
          MHFuture_8 |   .9841096   .0432297    -0.36   0.715      .902926    1.072593
          MHFuture_9 |   1.052066   .0623456     0.86   0.392     .9367007    1.181641
         MHFuture_10 |   .9879482   .0502213    -0.24   0.811      .894261    1.091451
         MHFuture_11 |   .9769366   .0536356    -0.43   0.671     .8772712    1.087925
         MHFuture_12 |   1.283914   .0746875     4.30   0.000     1.145566     1.43897
           MHClass_1 |   .8924394   .0675487    -1.50   0.133     .7693984    1.035157
           MHClass_2 |   .9810929   .0905225    -0.21   0.836     .8187896    1.175569
           MHClass_3 |   .7635181   .0687055    -3.00   0.003     .6400642    .9107833
               _cons |   .0166421   .0079904    -8.53   0.000     .0064941     .042648
----------------------------+----------------------------------------------------------------
Program                     |
          var(_cons)|   .2519834   .1259576                      .0945989    .6712088
------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    38.69 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7241
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     289.6
                                                               max =      4089

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(28)      =    720.84
Log likelihood = -2536.5344                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
        Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+----------------------------------------------------------------
                    Gender |   .7875384   .0670326    -2.81   0.005     .6665309    .9305146
                   GrpRace |   .7240404    .061509    -3.80   0.000     .6129869    .8552133
                   PrePost |   .9335216   .0738928    -0.87   0.385     .7993695    1.090187
                     Grade |   1.178213   .0269041     7.18   0.000     1.126644    1.232142
                 DosageGrp |   1.053792   .1177038     0.47   0.639     .8466027    1.311687
  MathAtttitudesweightedAvg |   1.696332     .13057     6.87   0.000     1.458788    1.972557
ScienceAttitudesweightedAvg |     2.5865   .1885545    13.04   0.000     2.242128    2.983765
EngTechAttitudesweightedAvg |    1.03283   .0842379     0.40   0.692     .8802473    1.211862
stCenturySkillsAttitudeswei |   .6233933     .05293    -5.57   0.000     .5278247    .7362655
              MHFuture_1 |   1.026301   .0551436     0.48   0.629     .9237177    1.140277
              MHFuture_2 |   .9773418   .0531729    -0.42   0.674     .8784889    1.087318
              MHFuture_3 |   1.058918   .0559471     1.08   0.279     .9547501    1.174451
```

```
          MHFuture_4 |   1.058393   .0523205     1.15   0.251     .9606576    1.166071
          MHFuture_5 |   1.157729   .0625104     2.71   0.007     1.041471    1.286964
          MHFuture_6 |   1.267752   .0743605     4.04   0.000     1.130074    1.422204
          MHFuture_7 |   .8967827   .0472743    -2.07   0.039     .8087527    .9943945
          MHFuture_8 |     .97061   .0433673    -0.67   0.504      .889227    1.059441
          MHFuture_9 |   1.054477   .0635019     0.88   0.378     .9370803    1.186582
         MHFuture_10 |   .9841475   .0506975    -0.31   0.756     .8896337    1.088702
         MHFuture_11 |   .9882506   .0549048    -0.21   0.832     .8862911     1.10194
         MHFuture_12 |   1.248247   .0733886     3.77   0.000     1.112386    1.400701
           MHClass_1 |   .8815048   .0678677    -1.64   0.101     .7580365    1.025084
           MHClass_2 |   .9772346   .0913981    -0.25   0.806     .8135575    1.173841
           MHClass_3 |   .7567478   .0690461    -3.05   0.002     .6328299    .9049307
            Adults_1 |   .9732964   .0490102    -0.54   0.591     .8818261    1.074255
            Adults_2 |   .9240499   .0489973    -1.49   0.136     .8328386     1.02525
            Adults_3 |   1.159354   .0600597     2.85   0.004     1.047418    1.283253
            Adults_4 |   .9796089   .0466995    -0.43   0.666     .8922253    1.075551
               _cons |   .0203413   .0106329    -7.45   0.000     .0073019    .0566658
----------------------------+----------------------------------------------------------------
Program                     |
          var(_cons)|   .287114   .1422051                      .1087581    .7579614
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    39.73 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression              Number of obs      =      7241
Group variable:         Program                Number of groups   =        25

                                               Obs per group: min =         1
                                                              avg =     289.6
                                                              max =      4089

Integration method: mcaghermite                Integration points =         7

                                               Wald chi2(29)      =    721.04
Log likelihood = -2536.3646                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------------
      Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+----------------------------------------------------------------
                  Gender |   .9971449   .4125208    -0.01   0.994     .4432151    2.243376
                 GrpRace |   .7230723   .0614649    -3.81   0.000     .6121039    .8541581
                 PrePost |    .934181   .0739541    -0.86   0.390     .7999189    1.090978
                   Grade |   1.178276   .0269083     7.18   0.000       1.1267    1.232214
                DosageGrp |   1.055213   .1178939     0.48   0.630     .8476947    1.313532
  MathAtttitudesweightedAvg |   1.696513    .130603     6.87   0.000     1.458912    1.972811
ScienceAttitudesweightedAvg |   2.587269   .1886144    13.04   0.000     2.242788    2.984661
EngTechAttitudesweightedAvg |   1.032041   .0841694     0.39   0.699     .8795818    1.210927
stCenturySkillsAttitudeswei |   .6233702    .052899    -5.57   0.000     .5278535     .736171
```

```
          MHFuture_1 |   1.025231   .0551286     0.46   0.643       .92268     1.13918
          MHFuture_2 |   .9784138    .053259    -0.40   0.688     .8794036    1.088571
          MHFuture_3 |   1.059714   .0560146     1.10   0.273     .9554231    1.175389
          MHFuture_4 |   1.057487   .0523041     1.13   0.258     .9597852    1.165135
          MHFuture_5 |   1.157539   .0624988     2.71   0.007     1.041302    1.286751
          MHFuture_6 |    1.26693   .0743168     4.03   0.000     1.129333    1.421292
          MHFuture_7 |   .8966804   .0472752    -2.07   0.039     .8086493    .9942948
          MHFuture_8 |   .9710066   .0433944    -0.66   0.510     .8895735    1.059894
          MHFuture_9 |   1.055175   .0635478     0.89   0.373     .9376941    1.187376
         MHFuture_10 |   .9841892   .0507003    -0.31   0.757     .8896703     1.08875
         MHFuture_11 |   .9873209   .0548833    -0.23   0.818     .8854044    1.100969
         MHFuture_12 |   1.249403   .0734922     3.79   0.000     1.113354    1.402077
           MHClass_1 |    .879864   .0678314    -1.66   0.097     .7564736    1.023381
           MHClass_2 |   .9759312   .0912944    -0.26   0.795     .8124427    1.172319
           MHClass_3 |   .7910979   .0938297    -1.98   0.048     .6270062    .9981336
            Adults_1 |   .9735761   .0490297    -0.53   0.595     .8820699    1.074575
            Adults_2 |   .9240476   .0489942    -1.49   0.136     .8328418    1.025241
            Adults_3 |    1.15912    .060052     2.85   0.004     1.047199    1.283003
            Adults_4 |   .9795901   .0466992    -0.43   0.665     .8922072    1.075531
                     |
              Gender |
          2. Female  |          1  (omitted)
                     |
   Gender#c.MHClass_3 |
          2. Female  |   .9164208   .1372302    -0.58   0.560     .6833309     1.22902
                     |
               _cons |   .0143391   .0114022    -5.34   0.000     .0030176    .0681374
----------------------------+------------------------------------------------------------------
Program                     |
          var(_cons)|   .2885051   .1426536                      .1094638    .7603905
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    39.85 Prob>=chibar2 = 0.0000

Mixed-effects logistic regression               Number of obs      =      7241
Group variable:         Program                 Number of groups   =        25

                                                Obs per group: min =         1
                                                               avg =     289.6
                                                               max =      4089

Integration method: mcaghermite                 Integration points =         7

                                                Wald chi2(29)      =    720.83
Log likelihood = -2536.5333                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------------
      Major_STEM_nonSTEM | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
----------------------------+----------------------------------------------------------------
                     Gender |   .7874679    .067043    -2.81   0.005     .6664441    .9304692
                    GrpRace |   .7381654   .3105522    -0.72   0.471     .3236281    1.683686
                    PrePost |   .9335137   .0738914    -0.87   0.385     .7993641    1.090176
                      Grade |   1.178242   .0269105     7.18   0.000     1.126661    1.232184
                 DosageGrp |   1.053926    .117749     0.47   0.638     .8466629    1.311928
  MathAtttitudesweightedAvg |   1.696398   .1305822     6.87   0.000     1.458833     1.97265
ScienceAttitudesweightedAvg |   2.586379   .1885602    13.03   0.000     2.241998    2.983659
EngTechAttitudesweightedAvg |   1.032894    .084253     0.40   0.692      .880285    1.211959
stCenturySkillsAttitudeswei |   .6233726   .0529298    -5.57   0.000     .5278047    .7362447
                 MHFuture_1 |    1.02624   .0551545     0.48   0.630     .9236378     1.14024
                 MHFuture_2 |   .9773499    .053173    -0.42   0.674     .8784968    1.087327
                 MHFuture_3 |   1.058963   .0559571     1.08   0.278     .9547774    1.174517
                 MHFuture_4 |    1.05847   .0523502     1.15   0.251      .960682    1.166213
                 MHFuture_5 |   1.157638   .0625357     2.71   0.007     1.041336    1.286929
                 MHFuture_6 |   1.267693    .074366     4.04   0.000     1.130005    1.422157
                 MHFuture_7 |   .8967916    .047275    -2.07   0.039     .8087604    .9944048
                 MHFuture_8 |   .9707106   .0434239    -0.66   0.506     .8892257    1.059663
                 MHFuture_9 |   1.054563   .0635325     0.88   0.378     .9371121    1.186734
                MHFuture_10 |   .9840903   .0507088    -0.31   0.756      .889557     1.08867
                MHFuture_11 |    .988273   .0549078    -0.21   0.832     .8863081    1.101968
                MHFuture_12 |   1.248255   .0733876     3.77   0.000     1.112396    1.400707
                  MHClass_1 |   .8814063   .0678919    -1.64   0.101      .757898    1.025042
                  MHClass_2 |   .9771825    .091399    -0.25   0.805     .8135047    1.173792
                  MHClass_3 |   .7597057   .0937944    -2.23   0.026     .5964235    .9676895
                   Adults_1 |   .9733055   .0490111    -0.54   0.591     .8818337    1.074266
                   Adults_2 |   .9240534   .0489959    -1.49   0.136     .8328447    1.025251
                   Adults_3 |   1.159307   .0600646     2.85   0.004     1.047362    1.283216
                   Adults_4 |   .9796061   .0466987    -0.43   0.666     .8922241    1.075546
                            |
                    GrpRace |
     1. Underrepresented  |          1  (omitted)
                            |
      GrpRace#c.MHClass_3 |
     1. Underrepresented  |   .9929212    .150436    -0.05   0.963     .7378201    1.336223
                            |
                      _cons |   .0201221   .0114977    -6.84   0.000      .006566    .0616662
----------------------------+----------------------------------------------------------------
Program                     |
                 var(_cons)|   .2869316   .1421677                      .1086497     .757754
------------------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    39.59 Prob>=chibar2 = 0.0000
```

//Parametric Test to Simplify Model

```
. testparm Grade MHFuture_1 MHFuture_6 MHFuture_11 MHClass_1 Adults_1 Adults_2
Adults_3 Adults_4

 ( 1)  [STEM_SE]Grade = 0
 ( 2)  [STEM_SE]MHFuture_1 = 0
 ( 3)  [STEM_SE]MHFuture_6 = 0
 ( 4)  [STEM_SE]MHFuture_11 = 0
 ( 5)  [STEM_SE]MHClass_1 = 0
 ( 6)  [STEM_SE]Adults_1 = 0
 ( 7)  [STEM_SE]Adults_2 = 0
 ( 8)  [STEM_SE]Adults_3 = 0
 ( 9)  [STEM_SE]Adults_4 = 0

           chi2(  9) =  221.52
         Prob > chi2 =    0.0000

Mixed-effects GLM                          Number of obs      =      7385
Family:              Gaussian
Link:                identity
Group variable:        Program              Number of groups   =        25

                                        Obs per group: min =         1
                                                       avg =     295.4
                                                       max =      4134

Integration method: mcaghermite                Integration points =         7

                                        Wald chi2(16)      =  12707.84
Log likelihood = -1751.2456                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------
                 STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+-------------------------------------------------------------
                  Gender |  -.0597525   .0082824    -7.21   0.000    -.0759856   -.0435194
                 GrpRace |   -.063254   .0084496    -7.49   0.000    -.0798149   -.0466931
                 PrePost |   .0261235   .0076481     3.42   0.001     .0111335    .0411134
                DosageGrp |   .0590279   .0114352     5.16   0.000     .0366154    .0814404
stCenturySkillsAttitudeswei |   .3194319   .0076694    41.65   0.000     .3044003    .3344636
               MHFuture_2 |    .008015   .0051575     1.55   0.120    -.0020934    .0181234
               MHFuture_3 |   .0317823   .0051955     6.12   0.000     .0215993    .0419652
               MHFuture_4 |  -.0333852    .004867    -6.86   0.000    -.0429243   -.0238462
               MHFuture_5 |   .1065651   .0048603    21.93   0.000     .0970391    .1160911
               MHFuture_7 |  -.0136647   .0050276    -2.72   0.007    -.0235186   -.0038108
               MHFuture_8 |   .0296209   .0041953     7.06   0.000     .0213983    .0378434
               MHFuture_9 |   .0163924   .0041633     3.94   0.000     .0082325    .0245523
              MHFuture_10 |   .0553093   .0047304    11.69   0.000      .046038    .0645806
              MHFuture_12 |   .1686005   .0053302    31.63   0.000     .1581535    .1790476
```

```
            MHClass_2 |   .1951618   .0087178    22.39   0.000     .1780753    .2122483
            MHClass_3 |   .1981032   .0092157    21.50   0.000     .1800408    .2161657
               _cons |   .5344002   .0448396    11.92   0.000     .4465163    .6222842
----------------------------+------------------------------------------------------------------
Program                     |
            var(_cons)|   .0037809   .0015104                      .001728    .0082727
----------------------------+------------------------------------------------------------------
          var(e.STEM_SE)|   .0936042   .0015427                      .090629    .0966771
------------------------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =    81.70 Prob>=chibar2 = 0.0000

//Parametric Test to Simplify Model

. testparm PrePost MHFuture_2 MHFuture_7

 ( 1)  [STEM_SE]PrePost = 0
 ( 2)  [STEM_SE]MHFuture_2 = 0
 ( 3)  [STEM_SE]MHFuture_7 = 0

           chi2(  3) =   19.21
         Prob > chi2 =    0.0002



Mixed-effects GLM                          Number of obs      =      7397
Family:              Gaussian
Link:                identity
Group variable:        Program              Number of groups   =        25

                                        Obs per group: min =         1
                                                       avg =     295.9
                                                       max =      4137

Integration method: mcaghermite                Integration points =         7

                                        Wald chi2(13)      =  12613.28
Log likelihood = -1782.2781                    Prob > chi2        =    0.0000
------------------------------------------------------------------------------------------------
                STEM_SE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------------+------------------------------------------------------------------
                 Gender |  -.0596303   .0082831    -7.20   0.000     -.075865   -.0433957
                GrpRace |  -.0631427   .0084706    -7.45   0.000    -.0797448   -.0465407
              DosageGrp |   .0589579   .0114589     5.15   0.000     .0364989    .0814168
stCenturySkillsAttitudeswei |   .3201616   .0076773    41.70   0.000     .3051143    .3352089
             MHFuture_3 |   .0302483   .0048182     6.28   0.000     .0208048    .0396917
             MHFuture_4 |  -.0328897   .0048602    -6.77   0.000    -.0424154   -.0233639
```

```
          MHFuture_5 |   .1057362   .0048572    21.77   0.000     .0962162    .1152563
          MHFuture_8 |    .028775   .0041745     6.89   0.000     .0205931     .036957
          MHFuture_9 |   .0159332   .0041753     3.82   0.000     .0077498    .0241167
         MHFuture_10 |   .0554787   .0046989    11.81   0.000     .0462691    .0646883
         MHFuture_12 |   .1679967   .0053063    31.66   0.000     .1575966    .1783968
           MHClass_2 |   .1965325   .0087089    22.57   0.000     .1794634    .2136016
           MHClass_3 |   .1986519   .0092384    21.50   0.000      .180545    .2167589
               _cons |   .5602925   .0439495    12.75   0.000     .4741531    .6464319
----------------------------+------------------------------------------------------------------
Program                     |
           var(_cons)|   .0041841   .0016345                      .0019457    .0089976
----------------------------+------------------------------------------------------------------
        var(e.STEM_SE)|   .0943008   .0015529                      .0913058     .097394
------------------------------------------------------------------------------------------------
LR test vs. linear regression:   chibar2(01) =    90.06 Prob>=chibar2 = 0.0000
```

Appendix E

Effect Sizes of Variables in Model I

The effect sizes of each variable in Model I of the analysis of the STEM Self-Efficacy composite score are presented here. Calculated as noted in Selya et al. (2012), the effect sizes were only calculated for Model I because the dependent variable of Model II, the choice of a STEM major (or not) was dichotomous and required a logistical form of the multilevel model. Only variables with a measurable effect size are presented here.

Variable	Effect Size
Gender	-0.003
Race	-0.005
Pre-Post	0.001
Dosage	0.004
21st Century Skills	0.234
Physics Career Interest	0.021
Biology & Zoology Career Interest	0.006
Veterinary Career Interest	-0.014
Mathematics Career Interest	0.049
Earth Science Career Interest	-0.002
Computer Science Career Interest	0.006
Medical Science Career Interest	0.003
Chemistry Career Interest	0.006
English Career Interest	0.103
Math Future Performance	0.057
Science Future Performance	0.053

Appendix F

Stata Code for Data Analysis

```
meglm  STEM_SE || Program:, family(poisson) link(log)
meglm  STEM_SE DosageCount Gender GrpRace || Program:, family(poisson) link(log)
meglm  STEM_SE DosageCount Gender GrpRace stCenturySkillsAttitudeswei || Program:,
family(poisson) link(log)
meglm  Major_STEM_nonSTEM || Program:, family(poisson) link(log)
meglm  Major_STEM_nonSTEM DosageCount Gender GrpRace || Program:, family(poisson)
link(log)
meglm  Major_STEM_nonSTEM DosageCount Gender GrpRace stCenturySkillsAttitudeswei ||
Program:, family(poisson) link(log)

mixed  STEM_SE Gender || Program:, base
predict fixed, xb
predict resid, residuals
twoway scatter resid fixed
kdensity resid, normal
pnorm resid
qnorm resid
iqr resid
gen sq_STEM_SE = (STEM_SE)^2
meglm  sq_STEM_SE || Program:, intmethod(mcaghermite)
predict fixed, xb
predict resid, residuals fixedonly

//effect size for Gender
meglm  STEM_SE || Program:, intmethod(mcaghermite)
estat icc
meglm  STEM_SE Gender || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender i.Race || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp MathAtttitudesweightedAvg ||
Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp ScienceAttitudesweightedAvg
|| Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp EngTechAttitudesweightedAvg
|| Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei ||
Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
```

```
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
matrix ab=e(b)
matrix list ab
global Vab = ab[1,28]
constraint 1 _b[/var(_cons[Program])]= ab[1,28]
meglm  STEM_SE GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Race
meglm  STEM_SE || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender i.Race || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp MathAtttitudesweightedAvg ||
Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp ScienceAttitudesweightedAvg
|| Program:, intmethod(mcaghermite)
```

```
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp EngTechAttitudesweightedAvg
|| Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei ||
Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
matrix ab=e(b)
matrix list ab
global Vab = ab[1,28]
constraint 1 _b[/var(_cons[Program])]= ab[1,28]
meglm  STEM_SE Gender PrePost Grade DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for PrePost
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
```

```
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Dosage--Grade was not significant so skipped
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade stCenturySkillsAttitudeswei MHFuture_1
MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for 21st Century Skills
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp MHFuture_1 MHFuture_2
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9
MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3 Adults_1
Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
```

```
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Physics Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Biology Career Interest--Enviro Skipped because non-significant
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
```

```
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Veterinary Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_5 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Mathematics Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_6 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
```

```
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Earth Science Career Interest--Medicine Skipped because non-significant
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Computer Science Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
```

```
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Medical Science Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Chemistry Career Interest
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
```

```
display "Effect size = $f2b"

//effect size for Engineering Career Interest--Energy Skipped because non-significant
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHClass_1 MHClass_2 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//effect size for Math Outcome Expectations--English skipped because non-significant
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_3
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"
```

```
//effect size for Science Outcome Expectations
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
coeflegend
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,27]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//Testing for variables that can be dropped from the model
meglm  STEM_SE Gender GrpRace PrePost Grade DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_6 MHFuture_7
MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12 MHClass_1 MHClass_2
MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:, intmethod(mcaghermite)
testparm Grade MHFuture_6 MHFuture_11 MHClass_1 Adults_1 Adults_2 Adults_3 Adults_4

meglm  STEM_SE Gender GrpRace PrePost DosageGrp stCenturySkillsAttitudeswei
MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_7 MHFuture_8
MHFuture_9 MHFuture_10 MHFuture_12 MHClass_2 MHClass_3 || Program:,
intmethod(mcaghermite)
testparm PrePost MHFuture_2 MHFuture_7

//Final version--Race Effect Size--testing to see if Effect Sizes change in simplified model
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program:, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program:, intmethod(mcaghermite) coeflegend
matrix ab=e(b)
matrix list ab
global Vab = ab[1,17]
constraint 1 _b[/var(_cons[Program])]= ab[1,17]
```

```
meglm  STEM_SE Gender DosageGrp stCenturySkillsAttitudeswei MHFuture_1 MHFuture_3
MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12 MHClass_2
MHClass_3 || Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,16]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//Test for 21st Century Effect Size--testing to see if Effect Sizes change in simplified model
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program:, intmethod(mcaghermite) coeflegend
meglm  STEM_SE Gender GrpRace DosageGrp MHFuture_1 MHFuture_3 MHFuture_4
MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12 MHClass_2 MHClass_3 ||
Program:, intmethod(mcaghermite) constraints(1)
matrix a = e(b)
matrix li a
global Va = a[1,16]
meglm  STEM_SE || Program:, intmethod(mcaghermite) constraints(1)
matrix null=e(b)
matrix li null
global Vnull = null[1,3]
global R2ab = ($Vnull - $Vab)/$Vnull
global R2a = ($Vnull - $Va)/$Vnull
display "Proportion explained full model = $R2ab"
display "Proportion explained reduced model = $R2a"
global f2b = ($R2ab - $R2a)/(1-$R2ab)
display "Effect size = $f2b"

//Adding interaction terms
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 Gender##c.MHClass_2 Gender##c.MHClass_3 || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 i.GrpRace##c.MHClass_2 i.GrpRace##c.MHClass_3 || Program:,
intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 i.DosageGrp##c.MHClass_2 i.DosageGrp##c.MHClass_3 || Program:,
intmethod(mcaghermite)
```

```
//Plotting Program Effectiveness before Level 2 effects
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program:, intmethod(mcaghermite)
predict re_Program, remeans reses(se_Program)
generate lower = re_Program - 1.996*se_Program
generate upper = re_Program + 1.996*se_Program
egen tag = tag(Program)
gsort +re_Program -tag
generate rank = sum(tag)
generate labpos = re_Program + 1.996*se_Program + .1
twoway (rcap lower upper rank) (scatter re_Program rank) (scatter labpos rank,
mlabel(Program) msymbol(none) mlabpos(0)), xtitle(rank) ytitle(predicted posterior mean)
legend(off) xscale(range(0 25)) xlabel(1/25) ysize(2)

//Model IV Effects at Level 2
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program: SchType, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program: SchType Rural_Urban, intmethod(mcaghermite)
meglm  STEM_SE Gender GrpRace DosageGrp stCenturySkillsAttitudeswei MHFuture_1
MHFuture_3 MHFuture_4 MHFuture_5 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_12
MHClass_2 MHClass_3 || Program: SchType Rural_Urban TitleI, intmethod(mcaghermite)

//Model I and II for RQ 2--duplicate to generate odds ratios
melogit  Major_STEM_nonSTEM || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender i.Race || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost || Program:,
intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade || Program:,
intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp || Program:,
intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg ||
Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
stCenturySkillsAttitudeswei || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei || Program:, intmethod(mcaghermite)
```

```
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
|| Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 || Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4 || Program:,
intmethod(mcaghermite)

//Simplifying the Model and Adding Interaction Terms for RQ 2
testparm PrePost DosageGrp EngTechAttitudesweightedAvg MHFuture_1 MHFuture_2
MHFuture_3 MHFuture_4 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHClass_1
MHClass_2 Adults_1 Adults_2 Adults_4
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4
Gender##c.MHClass_3|| Program:, intmethod(mcaghermite)
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4
GrpRace##c.MHClass_3|| Program:, intmethod(mcaghermite)

//Plotting Program Effectiveness for RQ2--required user written code to deal with missing values
xi: gllamm  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4, i(Program) adapt
nip(7) family(Gaussian) link(logit)
gllapred re_Program, u fsample
generate lower2 = re_Programm1 - 1.713*re_Programs1
generate upper2 = re_Programm1 + 1.713*re_Programs1
egen tag = tag(Program)
gsort +re_Programm1 -tag
generate rank2 = sum(tag)
generate labpos2 = re_Programm1 + 1.713*re_Programs1 + .1
twoway (rcap lower2 upper2 rank2) (scatter re_Programm1 rank2) (scatter labpos2 rank2,
mlabel(Program) msymbol(none) mlabpos(0)), xtitle(rank) ytitle(predicted posterior mean)
legend(off) xscale(range(0 25)) xlabel(1/25) ysize(2)
```

```
//Model IV for RQ 2
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4|| Program: SchType,
or
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4|| Program: SchType
Rural_Urban, or
melogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4|| Program: SchType
Rural_Urban TitleI, or
meqrlogit  Major_STEM_nonSTEM Gender GrpRace PrePost Grade DosageGrp
MathAtttitudesweightedAvg ScienceAttitudesweightedAvg EngTechAttitudesweightedAvg
stCenturySkillsAttitudeswei MHFuture_1 MHFuture_2 MHFuture_3 MHFuture_4 MHFuture_5
MHFuture_6 MHFuture_7 MHFuture_8 MHFuture_9 MHFuture_10 MHFuture_11 MHFuture_12
MHClass_1 MHClass_2 MHClass_3 Adults_1 Adults_2 Adults_3 Adults_4|| Program: SchType
Rural_Urban TitleI, or

hist  MathAtttitudesweightedAvg, freq normal xtitle("Mathematics Attitudes")
hist  ScienceAttitudesweightedAvg, freq normal xtitle("Science Attitudes")
hist  EngTechAttitudesweightedAvg, freq normal xtitle("Engineering & Tech Attitudes")
hist  stCenturySkillsAttitudeswei, freq normal xtitle("21st Century Skills Attitudes")
hist  STEM_SE, freq normal xtitle("Self-Efficacy Composite Score")
```

Appendix G

S-STEM Instrument

DIRECTIONS:

There are lists of statements on the following pages. Please mark your answer sheets by marking how you feel about each statement. For example:

Example 1:	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I like engineering.	❍	❍	❍	❍	❍

As you read the sentence, you will know whether you agree or disagree. Fill in the circle that describes how much you agree or disagree.

Even though some statements are very similar, please answer each statement. This is not timed; work fast, but carefully.

There are no "*right*" or "*wrong*" answers! The only correct responses are those that are true *for you*. Whenever possible, let the things that have happened to you help you make a choice.

PLEASE FILL IN ONLY ONE ANSWER PER QUESTION.

1. Math

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
1. Math is important for my life.	❍	❍	❍	❍	❍
2. Math has been my worst subject.	❍	❍	❍	❍	❍
3. I would consider choosing a career that uses math.	❍	❍	❍	❍	❍
4. Math is hard for me.	❍	❍	❍	❍	❍
5. I will need a good understanding of math for my future work.	❍	❍	❍	❍	❍
6. I am the type to do well in math.	❍	❍	❍	❍	❍
7. I can handle most subjects well, but I cannot do a good job with math.	❍	❍	❍	❍	❍
8. I am sure I could do advanced work in math.	❍	❍	❍	❍	❍
9. I can get good grades in math.	❍	❍	❍	❍	❍
10. I am good at math.	❍	❍	❍	❍	❍

2. Science

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
11. I am sure of myself when I do science.	❍	❍	❍	❍	❍
12. I would consider a career in science.	❍	❍	❍	❍	❍
13. I expect to use science when I get out of school.	❍	❍	❍	❍	❍
14. Knowing science will help me earn a living.	❍	❍	❍	❍	❍
15. I will need science for my future work.	❍	❍	❍	❍	❍
16. I know I can do well in science.	❍	❍	❍	❍	❍
17. Science will be important to me in my life's work.	❍	❍	❍	❍	❍

18. I can handle most subjects well, but I cannot do a good job with science.	❍	❍	❍	❍	❍
19. I am sure I could do advanced work in science.	❍	❍	❍	❍	❍

3. Engineering and Technology

Please read this paragraph before you answer the questions.

Engineers use math, science, and creativity to research and solve problems that improve everyone's life and to invent new products. There are many different types of engineering, such as chemical, electrical, computer, mechanical, civil, environmental, and biomedical. Engineers design and improve things like bridges, cars, fabrics, foods, and virtual reality amusement parks. Technologists implement the designs that engineers develop; they build, test, and maintain products and processes.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
20. I like to imagine creating new products.	❍	❍	❍	❍	❍
21. If I learn engineering, then I can improve things that people use every day.	❍	❍	❍	❍	❍
22. I am good at building and fixing things.	❍	❍	❍	❍	❍
23. Understanding engineering concepts will help me earn a living.	❍	❍	❍	❍	❍
24. I am interested in what makes machines work.	❍	❍	❍	❍	❍
25. Designing products or structures will be important for my future work.	❍	❍	❍	❍	❍
26. I am curious about how electronics work.	❍	❍	❍	❍	❍
27. I would choose a career that involves building things.	❍	❍	❍	❍	❍
28. I would like to use creativity and innovation in my future work.	❍	❍	❍	❍	❍

29. Knowing how to use math and science together will allow me to invent useful things.	❍	❍	❍	❍	❍
30. I believe I can be successful in a career in engineering.	❍	❍	❍	❍	❍

4. 21st Century Learning

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
1. I am confident I can lead others to accomplish a goal.	❍	❍	❍	❍	❍
2. I am confident I can encourage others to do their best.	❍	❍	❍	❍	❍
3. I am confident I can make moral decisions.	❍	❍	❍	❍	❍
4. I am confident I can produce high quality work.	❍	❍	❍	❍	❍
5. I am confident I can act responsibly.	❍	❍	❍	❍	❍
6. I am confident I can respect the differences of my peers.	❍	❍	❍	❍	❍
7. I am confident I can help my peers.	❍	❍	❍	❍	❍
8. I am confident I can include others' perspectives when making decisions.	❍	❍	❍	❍	❍
9. I am confident I can make changes when things do not go as planned.	❍	❍	❍	❍	❍
10. I am confident I can set my own learning goals.	❍	❍	❍	❍	❍
11. I am confident I can manage my time wisely when working on my own.	❍	❍	❍	❍	❍

12. When I have many assignments, I can choose which ones need to be done first.	❍	❍	❍	❍	❍
13. I am confident I can work well with students from different backgrounds.	❍	❍	❍	❍	❍

5. Your Future

Here are descriptions of subject areas that involve math, science, engineering and/or technology, and lists of jobs connected to each subject area. As you read the list below, you will know how interested you are in the subject and the jobs. Fill in the circle that relates to how interested you are.

There are no "*right*" or "*wrong*" answers. The only correct responses are those that *are true for you*.

	Not at all Interested	Not So Interested	Interested	Very Interested
1. Physics: is the study of basic laws governing the motion, energy, structure, and interactions of matter. This can include studying the nature of the universe. *(physicist, lab technician, astronomer, aviation engineer, alternative energy technician)*	❍	❍	❍	❍
2. Environmental Work: involves learning about physical and biological processes that govern nature and working to improve the environment. This includes finding and designing solutions to problems like pollution, reusing waste and recycling. (*pollution control analyst*, environmental engineer, or *scientist, erosion control specialist, energy systems engineer and maintenance technician)*	❍	❍	❍	❍
3. Biology and Zoology: involve the study of living organisms (such as plants and animals) and the processes of life. This includes working with farm animals and in	❍	❍	❍	❍

areas like nutrition and breeding. (biological technician, biological scientist, plant breeder, crop lab technician, *animal scientist, geneticist, zoologist)*				
4. Veterinary Work: involves the science of preventing or treating disease in animals. (veterinary assistant, veterinarian, animal caretaker, livestock producer)	❍	❍	❍	❍
5. Mathematics: is the science of numbers and their operations. It involves theory, computation, and algorithms used to solve problems and summarize data. (mathematician, statistician, accountant, applied mathematician, economist, financial analyst, market researcher, stock market analyst)	❍	❍	❍	❍
6. Medicine: involves maintaining health and preventing and treating disease. (physician's assistant, nurse, doctor, nutritionist, emergency medical technician physical therapist, dentist*)*	❍	❍	❍	❍
	Not at all Interested	Not So Interested	Interested	Very Interested
7. Earth Science: is the study of earth, including the air, land, and ocean. (geologist, weather forecaster, archaeologist, geoscientist)	❍	❍	❍	❍
8. Computer Science: consists of the development and testing of computer systems, designing new programs and helping others to use computers. (computer support specialist, computer programmer, computer and network technician, gaming designer, computer software engineer, information technology specialist)	❍	❍	❍	❍
9. Medical Science: involves researching human disease and working to find new solutions to human health problems. (clinical laboratory technologist, medical scientist, biomedical engineer, epidemiologist, pharmacologist)	❍	❍	❍	❍
10. Chemistry: uses math and experiments to search for new chemicals, and to study the structure of matter and how it behaves. (chemical technician, chemist, chemical engineer)	❍	❍	❍	❍

11. Energy: involves the study and generation of power, such as heat or electricity. (electrician, electrical engineer, heating, ventilation, and air conditioning (HVAC) technician, nuclear engineer, systems engineer, alternative energy systems installer or technician)	❍	❍	❍	❍
12. Engineering: involves designing, testing, and manufacturing new products (like machines, bridges, buildings, and electronics) through the use of math, science, and computers. (civil, industrial, agricultural, or mechanical engineers, welder, auto-mechanic, engineering technician, construction manager)	❍	❍	❍	❍

6. About Yourself

DIRECTIONS: In the following series of questions, you will skip certain questions based on how you answered previous questions. Make sure to read the directions in red that tell you about which questions to skip based on your answers.

1. How well do you expect to do this year in your:

	Not Very Well	OK/Pretty Well	Very Well
English Class?	❍	❍	❍
Math Class?	❍	❍	❍
Science Class?	❍	❍	❍

2. Do you plan to go to college?

❍ Yes
❍ No
❍ Not Sure

Please only answer Question 3 if your answer to Question 2 was "Yes."

3. Are you planning on going to a community college or four-year college/university first?

❍ Community College

❍ Four-year College

Please only answer Question 4 if your answer to Question 2 was "Yes" and your answer to Question 3 was "Community College."

4. Are you planning to attend a four-year college after you go to community college?

❍ Yes
❍ No

Please only answer Question 5 if your answer to Question 2 was "Yes."

5. Please list up to three colleges you are interested in attending.

College 1: _____

College 2: _____

College 3: _____

Please only answer Question 6 if your answer to Question 2 was "Yes."

6. Please list up to three college majors you are interested in.

Major 1: _____

Major 2: _____

Major 3: _____

Please only answer Question 7 if your answer to Question 2 was "No."

7. Are you planning on:

❍ Enlisting in the Military
❍ Finding a Job
❍ Other (Please List)

_____

8. Please list any other science, mathematics, engineering, or technology-oriented camps, clubs, or activities you have been involved in:

_____

_____

_____

9.

	Yes	No	Not Sure
Do you know any adults who work as engineers?	❍	❍	❍
Do you know any adults who work as scientists?	❍	❍	❍
Do you know any adults who work as mathematicians?	❍	❍	❍
Do you know any adults who work as technologists or technicians?	❍	❍	❍

Thank you for taking this survey! This is the end!