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Examining STEM Formative Experiences and College STEM Outcomes from a Social Cognitive Career Theory Perspective

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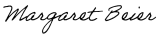

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Abstract

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College STEM (science, technology, engineering, and math) major matriculation and attrition decisions may be influenced by experiences occurring much earlier in students' lives than their contemporary college experiences. This research was guided by social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994), which describes how students develop career interests, make choices as a result of these interests, interpret their successes and failures, and ultimately make career decisions. Although many studies of STEM interest, self-efficacy, and academic behavior have been conducted on high school and college students, childhood experiences have been less studied, despite the emphasis that SCCT places on early life experiences. Using a biodata measure that incorporated background influences and learning experiences factors previously developed from semi-structured interviews with STEM students, I conducted a two-part study. Study 1 entailed an exploratory factor analysis of the biodata measure and other constructs on underprepared STEM students at Rice (N = 154). After refining the biodata measure, a confirmatory factor analysis and structural equation model were conducted on a separate sample of first-year Rice students in Study 2 (N = 175). Findings from both studies provide support for a seven-factor model and a reasonable fit with a modified structural equation model based on SCCT. These seven factors comprise three background influence factors (general parent support, STEM parent support, and teacher support) and four formative experience factors (math extracurricular activities and competitions, science extracurricular

activities and competitions, proactive STEM behavior, and STEM knowledge). All were significant in the full structural equation model except teacher support, and several factors showed gender and race effects. Further research will be necessary to refine and validate this measure on other samples and develop greater insight into the relationships between this new measure and STEM self-efficacy, STEM interest, career outcome expectations, initial college major, and intended college major. Ultimately, these studies may guide future research that uses a theoretical approach to explore the STEM experiences of students at all education levels, as well as define factors that schools and program administrators may find valuable to explore in future STEM interventions.

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CHAPTER 1: INTRODUCTION

Research Purpose

College students' retention in STEM (science, technology, engineering, and math) majors has been a major national policy concern in the United States for decades. Approximately one-third of students who matriculate as STEM majors in college leave STEM within a year, while less than 12% switch into STEM during the same time period (National Science Board, 2018). STEM attrition is a particular concern for underrepresented minority students, as well as female students in the natural sciences, engineering, and math. Many reasons have been proposed for this gap, ranging from systemic barriers to explicit discrimination to cultural, demographic, and gender differences in values and interests. Many studies on STEM students regarding STEM interest, career plans, and long-term behaviors have been conducted on experiences college students have during high school and college, but few examine life experiences occurring before high school. However, research shows that interests and self-efficacy in STEM topics begin to diverge by as early as mid to late elementary school, declining for many students as well as showing pronounced gender and race effects (with greater declines for females and underrepresented minorities). In addition to having different demographic backgrounds, students might also have different background influences and learning experiences that impact their choices and behavior years later (Evans, 2006). Exploring the link between early experiences and STEM outcomes may be worthwhile in developing greater insight into the factors that predict long-term success and retention in STEM.

Hypotheses

The hypotheses to be tested in Study 1 include:

1. *The biodata measure will demonstrate moderate (approximately r = .30) convergent validity with openness to experience.*
2. *The biodata measure will demonstrate discriminant validity with agreeableness.*
3. *The "Proactive Behavior" biodata factor will demonstrate moderate convergent validity with proactivity.*
4. *The "Encouragement and Exposure to STEM" and "Receiving Help in School Settings" factors will demonstrate moderate convergent validity with school quality, teacher helpfulness, and book availability.*
5. *The biodata measure will demonstrate discriminant validity with the number of elementary schools that students attended.*
6. *The data will show evidence of six distinct factors (Exposure and Encouragement for STEM, Being Provided STEM Resources, Having Hands-on STEM Experiences, Participating in STEM Competitions, Receiving Help on School Assignments, and Proactive or Voluntary STEM Behaviors), with individual items loading onto the a priori anticipated factors.*

Research Questions

The research questions to be examined in Study 2 include:

1. *Which background influence themes predict students' second-semester major?*
2. *Which formative experience themes predict students' second-semester major?*
3. *How well do the data obtained from the surveys and students' academic records fit the proposed model based on social cognitive career theory?*

Research Overview

To examine the impact of early life experiences on STEM outcomes, I conducted two studies. Both studies were designed around the validation of a measure of STEM formative experiences developed from earlier semi-structured qualitative interviews with STEM students, framing the measure as part of social cognitive career theory.

In Study 1, I conducted an exploratory factor analysis on the measure and re-categorized and re-named several of the *a priori* item constructs, as well as altering some items in the original version of the measure. I also explored the convergent and discriminant validity of the measure against several established measures, including incorporating several broader measures of educational quality and access to resources in order to consider student context more broadly than traditional SCCT would dictate. In Study 2, I conducted a confirmatory factor analysis on the refined version of the measure and incorporated it into a structural equation model to test its fit against the expected relationships the SCCT framework illustrates. To minimize common method bias, I also incorporated students' academic records from the registrar's office, as well as objective academic data in the form of self-reported high school classes taken and standardized tests scores.

Theoretical Background

These studies are based on social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994), which incorporates early life experiences into a career-centered psychological model and frames STEM actions and decisions that occur during high school, college, and students' eventual career as the result of these early experiences. Exploring early STEM experiences using a theoretical model that encompasses early experiences may bring insight into the processes and constructs that impact students from early childhood until college. Research on

STEM formative experiences has been dominated by studies of much older students, when SCCT research would propose that much of these children's values, goals, and outcomes have already been established. The first three stages of the framework (acquiring self-efficacy, developing career-related interests, and building career-related aspirations) take place primarily during a child's elementary and middle school years (Lent et al., 1999). In reality, relationships between variables in this model are reciprocal (Halpern et al., 2007), but SCCT provides a proposed order to these relationships, which enables testing of the model empirically.

Contributions to Research

The theoretical contributions of these studies include the development and validation of a STEM formative experiences biodata questionnaire that is based on established theory and qualitative data provided by STEM students themselves rather than the atheoretical rational or empirical measure development approaches more common to biodata measure development. Another contribution is the testing of a model designed for general academic behavior and career interests on STEM constructs to determine whether the anticipated relationships are supported in a specific domain. These studies will determine whether the biodata measure contributes significantly to a structural equation model that also includes other, more proximal STEM psychological constructs. Finally, this study offers the opportunity for researchers to better understand the trajectory of students' college major decisions by assessing not only their matriculation major but also how their major changes over their first year in college.

Contributions to Practice

The practical implications of these studies include validating a scale that may be used on other student samples to determine which biodata factors consistently predict STEM outcomes across samples, explore subgroup differences in early STEM experiences, and identify which

students may have received the least exposure to STEM topics in elementary school compared to their classmates. Findings from this and the future studies this research generates will provide insight into influences and experiences that might guide parents and teachers in fostering increased STEM interest, self-efficacy, and career outcome expectations, as well as ultimately influencing students' college major decisions. Schools in districts with limited resources might use these findings to guide where to invest their time and resources to generate the greatest impact on student STEM outcomes, and school administrators can also provide guidance to teachers on any instructional, classroom, or curriculum changes that might be worthwhile. Parental education efforts might focus on teaching parents how to interact with and encourage their children in STEM content areas. Finally, studies that capture specific experiences of students and show criterion validity in predicting choice goals and choice actions may serve as directions for future interventions (see Lent & Brown, 2006).

CHAPTER 2: LITERATURE REVIEW

This literature review incorporates two distinct but related themes. The first section reviews the constructs relevant to social cognitive career theory (SCCT), primarily oriented toward a STEM context. The second section covers the constructs relevant to developing and persisting in STEM, as well as the psychological and societal factors that might contribute to greater barriers for underrepresented groups in STEM fields. Additional factors that were explored in the initial biodata measurement development process that preceded Study 1 are discussed in the following chapter.

Social Cognitive Career Theory

Social cognitive career theory is framed around distinct constructs that represent students' self-concepts and cognitions in the context of students' social lives and offers an order to test theory and the relationships between constructs (Lent et al., 1994). Although the framework has a clear psychosocial focus, it is also designed to incorporate affective, biological, and developmental factors and understand the core pathways through which all these influences jointly function (Lent et al., 1994). See Figure 1 for a simplified version of the SCCT model, adapted for a STEM context.

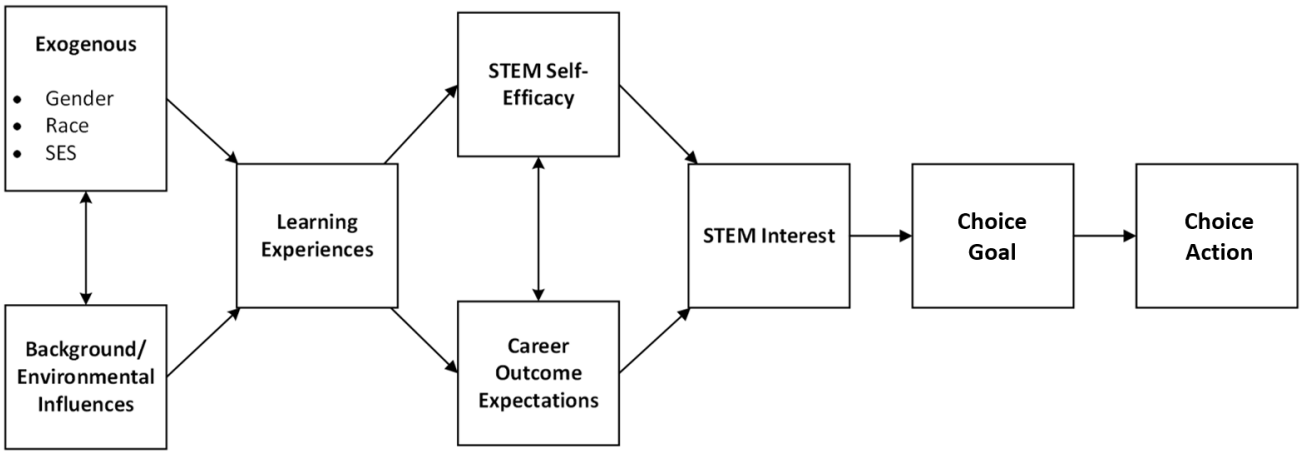

Figure 1. SCCT model, adapted for a STEM context

Formative experiences. Influential childhood experiences may be both specific events that students experienced (which I conceptualize as learning experiences in the SCCT model) or a more general context of how background, environmental or other social factors impacted students' childhoods (which I conceptualize as background influences; Miller & Votruba-Drzal, 2013). Research on students' identity and interest in STEM topics finds that preferences are often "set" by the end of middle school, and that otherwise similar students diverge markedly in math performance by the end of elementary school (Lent et al., 1991). Trajectories in early science interest may be especially important to consider, as most students report being interested in science until about ten years old, and then interest begins to decline for many students, especially girls (Lindahl, 2007). Early science interest is critical for influencing later STEM choices. For example, a longitudinal study of students from ages 12 through 16 found that students' perceptions of science were largely established by the age of 14 (Lindahl, 2007). In a study of English STEM practitioners, one-third reported that they began considering a STEM career by the age of 11 and another one-third by age 14 (The Royal Society, 2006). In a study of

gifted students, researchers found that students had decided whether they enjoyed science by the age of nine (Joyce & Farenga, 1999). Examining factors that occurred before students entered high school might provide insight into how and why student career interests in math and science were established.

Despite the evidence for the impact of early STEM experiences on long-term STEM outcomes, much of the research on STEM education has evaluated contemporary college experiences, after many important educational and career goals have already been established (Wang & Degol, 2013). Researchers such as Farenga and Joyce (1999) have discussed the limited impact that high school interventions might have. Further, even when early STEM experiences are studied, researchers have varied in defining what constitutes "early" experiences, often including high school experiences in their definitions. For example, researchers have operationalized these experiences as high school experiences only (e.g. Dika & D'Amico, 2016), experiences up to age 12 (e.g. Coats & Overman, 1992), and elementary through high school events (e.g. Bulunuz & Jarrett, 2010). Due to the evidence that STEM identity and interests before students' teenage years strongly correlate to longer-term STEM outcomes, STEM formative experiences are defined in this paper as those occurring before middle school in one or more STEM domains.

STEM self-efficacy. In the SCCT framework, self-efficacy is a result of students' background influences and learning experiences. It is a belief that one has the ability to perform a task to meet one's own performance objectives (Bandura, 1994). *STEM self-efficacy* reflects students' beliefs about their competence to succeed in STEM domains (Perez et al., 2014). Students who have high self-efficacy are more likely to seek out other approaches if they fail at a task, to engage and persist in academic tasks, and to respond to academic setbacks in an adaptive

way (Bandura, 1997). Many studies on the self-efficacy of students in STEM have shown correlations between important factors in the SCCT model. For example, the science self-efficacy of students correlates with achievement and engagement in science. In a sample of 319 middle school students, science self-efficacy explained 34% of the variance ($\beta = .48$) in students' science grades (Britner & Pajares, 2006). A path analysis of 288 eleventh and twelfth grade students found that science self-efficacy directly predicted students' anticipated likelihood of choosing STEM majors or graduating in a STEM field (Lau & Roeser, 2002). In another study, self-efficacy was a large ($r = .55$) predictor of sixth grade science students' final class grades (Chen & Pajares, 2010). Clearly, self-efficacy plays an important role in predicting later STEM outcomes.

Notable from the perspective of studying early life experiences, Bandura's (1997) model proposes four sources of self-efficacy. *Mastery experiences* refer to how students interpret the results of past actions, use the interpretations to understand their capabilities, and act according to this understanding. *Vicarious experiences* refer to students observing others perform a task and judging their own likelihood of success based on their observations, particularly when they are unfamiliar with the task or uncertain about their abilities. *Social persuasion* refers to judgments that others make, both verbally and nonverbally, that impact the student's perception of the attainability of success. It is more powerful at weakening self-efficacy than strengthening it. Finally, *physiological states* refer to students' perceptions about their stress, emotional arousal, anxiety, and mood in indicating their likelihood of success. In the same study of middle school students by Britner and Pajares (2006), mastery experiences were the only significant predictor of the four on students' science self-efficacy. A meta-analysis by Sheu et al. (2018) found a two-factor solution for the sources of self-efficacy of STEM students, with mastery

experiences, persuasion, and physiological state contributing to a single “direct personal experiences” factor, and a second factor resulting from vicarious experiences. From the perspective of this study, it may be relevant to understand how different types of early STEM experiences may be influential.

Career outcome expectations. Outcome expectations are the effect one believes an action will have on furthering one accomplishing his or her goals (Lent et al., 2008). In Bandura's (1997) model, self-efficacy represents one’s ability to perform a task; outcome expectations represent the expected results from performing that task. In the context of STEM research, *career outcome expectations* refer to what students believe the outcomes of participating in STEM activities and STEM achievement will be and whether the outcomes will further the students’ chances of meeting their career goals. In the SCCT model, career outcome expectations are the other result (along with self-efficacy) of the background influences and learning experience students have in STEM domains. A study of the development of physics interest over time found that students make judgments of the appropriateness of a working in a physics career as early as age nine (Farenga & Joyce, 1999). Students’ perceptions of their parents’ beliefs and expectations in their STEM ability and performance (potentially reflecting earlier influences and experiences these children had), predict student STEM outcomes, including their career choices (Hazari et al., 2010). Similarly, a study of 318 sixth graders found that students’ perceptions of their parents’ support for STEM predicted student career expectations, with self-efficacy mediating this relationship (Turner et al., 2004). To the extent that students’ perceptions are the result of their interpretations of earlier life experiences, one would expect these experiences to impact students’ career outcome expectations.

STEM interest. Interest predicts learning and retention of content, and students with

greater interest in a topic require fewer resources to learn new material (Sansone & Thoman, 2005). The development of interest over time may predict students' career outcome expectations, (although students' identity may mediate this relationship; Hazari, Sonnert, Sadler, & Shanahan, 2010). Interest is context-specific, meaning that one's interest is targeted at an activity, topic, object, or goal (Renninger, 2000). Researchers such as Milner, Horan, and Tracey (2014) have found support for STEM interest, which is students' interest in one or more STEM domains, being a general construct rather than differing significantly between STEM fields. Maltese and Tai (2010) found that interest in math and science as a general construct predicted enrollment in math and science classes in high school, which in turn predicted STEM degree persistence. Further, although it did not reflect the hypothesized order of the SCCT model, in a path analysis of the science interest and science self-efficacy of 86 eighth grade students, both science interest and science self-efficacy predicted students' outcome expectations, which in turn predicted whether they had science career goals (Hiller & Kitsantas, 2014). As students leave elementary school and enter middle school, their interest in a topic tends to evolve from interest as primarily an affective, or emotionally enjoyable, experience to a perception that also encompasses evaluative beliefs about the meaningfulness, value, and autonomy allowed in the domain (Frenzel et al., 2012). This finding reflects the proposed association in the SCCT model between career outcome expectations (a utility judgment) and STEM interest development.

Factors Contributing to Underrepresentation in STEM

Females and underrepresented minorities are underrepresented in STEM majors and careers (National Science Board, 2015), and their attrition rates from STEM majors are particularly concerning. Overall, about one-third of STEM matriculants leave STEM majors within their first year. Approximately one-fifth of underrepresented minority students

successfully graduates with a STEM degree, compared to one-third of White and almost of half of Asian students (Higher Education Research Institute, 2010). It is possible that higher barriers or disadvantages that underrepresented minority students face on their journeys to entering college and graduating with a major in STEM contribute to this underrepresentation. Further, although overall gender participation in STEM majors is only slightly skewed toward males, the proportion of female graduates is much lower in certain fields, such as computer science and engineering (which are roughly 20% female) compared to the biological and health sciences (females earn almost 60% of biological sciences degrees; National Science Board, 2018). Both underrepresented minorities and female students undoubtedly have different social, psychological, and institutional experiences on their educational journeys in STEM than non-underrepresented minority male students. Certain predictors may be worth exploring in context of the impact they make on students' long-term STEM matriculation and retention decisions.

School quality. School quality strongly influences children's academic success (Kitano & Lewis, 2005). Concerns about weak school quality apply to underrepresented minority students in particular, who are disproportionately from low SES backgrounds (Estrada et al., 2016). Schools in high-poverty areas and with high proportions of underrepresented minority students are more likely to be lower quality than less economically disadvantaged schools and those with high proportions of Asian or White students (Borman & Overman, 2004; Kozol, 1991). Better schools are safer and have more highly trained and effective teachers (Hamre & Pianta, 2005), better institutional facilities, and wider and more advanced course options (Eamon, 2005). Lower quality schools have lower expectations of their students, creating a self-fulfilling prophecy and predicting worse academic outcomes (Maulucci, 2010). As a result of the influence of low SES backgrounds and attending weaker schools, many underrepresented

minority students undoubtedly have different formative experiences than students from higher SES backgrounds and those who attend more challenging schools.

Science education may be particularly weak at under-resourced schools. These schools cannot provide the same highly educated teachers, course material, and interactive activities that students from schools with greater resources receive. For example, at many under-resourced elementary schools, science instruction is almost entirely absent, and schools at all grade levels often have inadequate science lab equipment and facilities (Maulucci, 2010). Many teachers at low performing schools believe that science is not a high priority for school administrators. Further, teachers unfamiliar with course content, as many elementary and middle school teachers are with science, tend to rely more on the curriculum's provided instructional material than the adaptations and enriched assignments they make when teaching content with which they are more familiar (Brown & Edelson, 2003). Because lower SES schools have less qualified and experienced science teachers, students may be learning science in ways that do not go into depth, as they do not have access to lab equipment and activities.

Classroom experiences. Female and underrepresented minority students have different elementary school classroom experiences than White males. For example, both groups face the continued use of science textbooks that describe and provide photos of only White male scientists (Brush, 1991). Girls also have an array of socially driven STEM experiences different from boys in elementary school. For example, girls are more likely to wait for teacher instructions to interact with science equipment and to spend less time using the equipment than boys when there is not enough equipment for every child (Fadigan & Hammrich, 2004). Over the years of school, this can add up to a significant difference between boys and girls on the amount of time they spend interacting with STEM tools in the classroom. Science activities outside of

school also allow students to develop deeper science competencies than science taught in highly-controlled school settings (Hiller & Kitsantas, 2014). However, girls tend to participate less in these extracurricular science activities (Catsambis, 1995), meaning that girls have fewer opportunities to develop a deep understanding of science. Female students also must adapt to science curricula that is typically oriented toward male students. For example, in science textbooks, physical science examples are typically given in male-oriented terms, such as describing how guns or cars work (Sadker & Sadker, 1994). In general, girls face years of STEM experiences in the classroom that cater instruction and curriculum toward boys.

Regardless of school quality, underrepresented minority students face discrimination in the classroom. They are more likely to be placed on course tracks lower than their true ability level, and teachers are more likely to have lower academic expectations of them and provide them less positive and neutral feedback than White students (Tenenbaum & Ruck, 2007). Minority students are expected to communicate and ask questions in the classroom in line with how mainstream classroom culture dictates rather than their own natural communication approaches (Gee et al., 1992). This barrier is a particular concern in science classes, where students from cultural backgrounds that emphasize spirituality, interconnectedness, and purpose may find themselves alienated. Science instruction in mainstream schools tends to be descriptive and realistic rather than emotional or figurative, and it tends to distance itself from descriptions of human experiences (Lemke, 1990). Consequently, students from underrepresented groups must navigate an entirely different pedagogy than one that reflects their own understanding of the world. Further, teaching approaches generally focus on what students do and what they are capable of doing, ignoring the context of students' motivation, choices, and values and belief systems (Boykin, 1986). Because science may be inherently less accessible to many

underrepresented minority students, these students might require experiences or additional support non-underrepresented minority students do not need to uphold their science interest in the face of systemic challenges.

Stereotype threat. Both underrepresented minorities and females in STEM face *stereotype threat*, in that they fear conforming to negative stereotypes about a group with which they identify on performance in STEM domains, particularly math (Valla & Williams, 2012). This fear of being evaluated reduces students' enjoyment of the topic and triggers physiological stress responses, ultimately producing underachievement (Good et al., 2003). Group composition alone is sufficient to trigger stereotype threat (Inzlicht & Ben-Zeev, 2000), meaning that being underrepresented in a STEM class (as many female and underrepresented minority students are) is sufficient for students to feel threatened, depleting their cognitive resources and their ability to perform well on the task. Research has suggested that students first become vulnerable to stereotype threat around the ages of 11 or 12 (Good et al., 2003), indicating that students may have significant experiences relevant to math achievement beginning in middle school. Underperforming in math has negative implications for STEM achievement, because math skills form the foundation of all STEM fields and are crucial for academic success (Shaw & Barbuti, 2010). Useem (1992) identified seventh grade (and the experiences leading up to seventh grade math achievement) as critical for longer-term math outcomes, as this is the year in which students are traditionally assigned various math "tracks." Students in the most advanced tracks are often assigned pre-algebra in seventh grade, algebra in eighth, and will be prepared to take calculus in high school. Students on the "regular" track or remedial track must take other math classes before they qualify to take calculus in high school, delaying or even preventing them from taking calculus and limiting their math preparation for college coursework.

During early childhood, students do not show gender differences in math ability (Spelke, 2005). However, as they get older, girls begin to self-report lower math ability than boys with the same objective math achievement (C. Hill et al., 2010), a self-perception that continues into college (Pajares & Miller, 1995) and has been linked to longer-term career intentions. For example, a study of 86 women in math-heavy majors found that greater beliefs that gender differences on math performance were based on legitimate differences in innate ability correlated with lower confidence in math ability (r = -.21) and lower intentions to pursue graduate school in their major (r = -.26; Schmader, Johns, & Barquissau, 2004). Another study of 56 male and female college students who were matched on high math performance, similar calculus backgrounds, and high math perceptions and values found that men significantly outscored women on a difficult math test but not an easy one, which may have activated their stereotype threat (Spencer, Steele, & Quinn, 1999). In a study of 174 college students enrolled in upper-level mathematics classes, women's calculus test performance was higher in the "stereotype nullifying" condition, in which the test was preceded by a statement explaining that the test did not show gender differences (Good et al., 2008).

Underrepresented minority students also face stereotype threat. Asking students their race before administering tests ostensibly designed to test intelligence creates stereotype threat (Steele & Aronson, 1995). In a national data set of 28,240 high school seniors, anxiety explained significant differences in math achievement by race (η^2 = .23 for Black versus White scores and η^2 = .21 for Hispanic versus White scores; Osborne, 2001). In a study of 51 fourth through sixth grade students, Alter, Aronson, Darley, Rodriguez, and Ruble (2010) found that underrepresented minority students who had to report their race before taking a math test (activating their stereotype threat) performed better if they were told that the test would help

them do better in school than if told it was designed to test their math ability. Underrepresented minority students, those from low SES backgrounds, and those from non-English speaking households may all be at a disadvantage in terms of math skills entering kindergarten. Even if students' skills progress at the same rate as other students, they will remain behind students who entered with higher levels of math foundational knowledge (Capraro et al., 2009). Cumulatively, students from underrepresented minority backgrounds are likely to enter elementary school with weaker math backgrounds and also face stereotype threat in their math ability.

Differences in STEM interest. Interest in a domain refers to how much one personally enjoys or likes performing tasks in that domain (Eccles & Wigfield, 2002). Some researchers have linked disproportionate gender attrition rates to gender differences in career and domain interest. For example, a meta-analysis of sex differences within STEM fields attributed females' greater representation in the biological and health sciences to a higher "people orientation" and males' greater representation in the natural sciences and engineering to greater "things orientation," rather than differences in quantitative ability (Su & Rounds, 2015). However, because the relationships between interest in science and math interest, ability, and time dedicated to pursuing math and science are reciprocal, it is difficult to ascertain whether true differences in mathematics ability exist (Halpern et al., 2007), and to what extent differing interests between males and females explain STEM attrition rates. Further, girls may perceive identity conflicts between their science or math interest conflicts and their social identity as girls. For example, in focus groups on science interest with 10 and 11-year old students, Archer et al. (2010) found that girls' declining interest in science beginning in middle school may be partly explained how science is taught and perceived. Both boys and girls described science in traditionally masculine language (e.g. "dangerous," "risky"). If girls perceive an incongruence

with their science or math interest and their social identity, they might withdraw from or lose interest in topics that do not align with that identity.

Students from many underrepresented minority backgrounds, especially Hispanic and Native American students, are generally raised in and value *communal goals* (which are aimed at helping a collective or serving a larger community) over *agentic goals* (which benefit the individual, such as obtaining a high income or working in a prestigious field; Abele & Wojciszke, 2007). Females also tend to endorse communal goals more so than males (Diekman et al., 2010). However, STEM fields have traditionally emphasized agentic goals (e.g. by providing opportunities to demonstrate individual competence, compete with others, or be self-directed) creating a disconnect between certain students' value systems and their STEM interest (Diekman et al., 2011). Many students view STEM fields as lacking in opportunities for collaboration or helping a larger community (Allen et al., 2015), which may drive them away from developing a strong interest in STEM or continuing to pursue their STEM interest (Grandy, 1998). Underrepresented minority students also often take science and math classes that use textbooks, curricula, and lab activities designed by those with no understanding of these students' cultural contexts (Boykin, 1986). These classes, often the result of standardization intended to make schooling more equitable, in practice may hinder children by teaching them a narrow, Eurocentric conceptualization of science (Seiler, 2001). Conceivably, students who can link their STEM interest to their own value and belief systems might be more resilient in maintaining their STEM interest.

Summary

In this literature review, I explored the constructs relevant to social cognitive career theory and how they might be adapted to fit a STEM-specific context, in order to provide a

theory-driven understanding of STEM formative experiences and subsequent personal and professional decisions. I then reviewed critical barriers to certain students' successful STEM degree completion and decision to enter STEM fields, which may interact with school, social, individual, and other formative experiences. Finally, this review informs the design of the following studies by establishing that understanding STEM formative experiences is critical to fully capture their role and importance in the social cognitive framework, yet these experiences are underexplored in both broader STEM and SCCT research. I propose the development of a theory-driven retrospective measure to address this gap in current STEM research.

CHAPTER 3: STEM FORMATIVE EXPERIENCES MEASURE DEVELOPMENT

The line of research I explore in Studies 1 and 2 builds on a biodata measure of formative experiences I developed from data gathered on the early STEM experiences of 35 Rice undergraduate (freshman or sophomore) STEM students from March through May 2018 (Bradford, 2018). Biographical data, or biodata, consists of measures of one's various backgrounds and experiences (Owens & Schoenfeldt, 1979). These measures, which originally only collected basic objective data such as respondents' number of siblings and education level, more recently have been designed to capture detailed characteristics, such as respondents' experiences, preferences, hobbies, and interests (Schmitt & Golubovich, 2013). The core attribute of biodata (and what separates it from other measures) is that it captures historical events or experiences (Mael, 1991), which provides the means to study early life experiences in the following studies. Biodata has been shown to predict a wide range of outcomes relevant to the SCCT model, such as behavior and attitudes (e.g. Schmitt & Golubovich's, 2013, study on job turnover and attitudes), interests (e.g. science teachers' childhood play experiences predicted their science interest and confidence in teaching ability; Jarrett, 1999), and motivation (e.g. Mumford et al., 1990). Although they were not referring to early experiences in particular, Lent and Brown (2006) have discussed how developing scales that reflect the supports and barriers students believe they will encounter might be relevant to predicting choice goals and actions. As the authors note, however, these constructs have rarely been explored to determine the impact of specific barriers and supports.

Biodata, like any other form of data collection that is based on self-reported narratives, may omit or alter objective occurrences. However, this subjectivity is not necessarily a drawback, and narrative data provide their own value to this line of research. Individual

narratives are the result of one's internal system to interpret reality and generate meaning, which then impacts one's self-concept (Shamir & Eilam, 2005). On a psychological level, an individual's behavior and cognitions are filtered through the lens of the meaning and impact they assign their experiences. People's narratives about their lives, or their *life stories,* begin to cohere in late adolescence, and although these life stories are based on real events, they are also influenced by the person's cultural norms, reconstructed to create a deeper sense of unity of one's past, and interpreted to provide meaning and purpose for the person's life (McAdams, 2001). Because students' life narratives are ultimately a reflection of their cognitions and beliefs about their past, measures that require retrospective self-reflection may be able to capture information that more directly influences people's current experiences than a literal report of everything that happened in their past.

Qualitative Data Analysis

Biodata measurement as a field originally used items generated either rationally by subject matter experts (meaning the items are designed based on what experience has shown the experts to be important in predicting outcomes) or empirically (meaning the items are designed to correlate with outcomes of interest irrespective of theoretical rationale). However, more recently researchers have begun writing items designed to capture certain constructs determined *a priori* (Schmitt & Golubovich, 2013). Both theory-driven and narrative-driven biodata item generation approaches are well-established procedures (Mumford, Costanza, & Connelly, 1996). In either case, item generation should establish construct validity to allow meaning and inferences to be drawn from test scores, which means that items should be developed based on theoretical rationale (Messick, 1995).

The scale development process in this study involved both transcription and then independent qualitative coding of all transcripts by two undergraduate research assistants (see Bradford, 2018 for more detail). I used a thematic analysis process, a qualitative analysis approach designed to identify recurring concepts between different participants that would be unlikely to be identified from analyzing a single interview (Nowell et al., 2017). Researcher judgment is required in the process of identifying themes, because although the prevalence of a concept among multiple interviewees and the length of discourse provided by interviewees can guide thematic identification, the goal of thematic analysis is not to provide rules or "thresholds" (Braun & Clarke, 2006). Including only the codes that both URAs identified and using the analytic memos each URA supplied about their thought process while coding and my follow-up notes from one-on-one debrief meetings after the coding process was completed, I identified five preliminary themes, each with two sub-themes to provide further structure to the data, to explore via biodata item creation and further analysis. I used an essentialist perspective when building themes, which is designed to identify the experiences, cognitions, and realities of participants (rather than the more societally-focused "constructionist" approach; Braun & Clarke, 2006), because this analysis was ultimately designed to lead to biodata item creation about the personal experiences of respondents. Further, because I was exploring an understudied research area (STEM formative experiences), my approach to theme development was inductive, in that I reviewed the data and codes and developed themes without attempting to "fit" them into a specific theoretical model.

I excluded codes that only addressed a specific interviewee's life circumstances (e.g. one student had an academic rival, which no other interviewees reported) because the purpose of thematic analysis is to link concepts shared among multiple participants. Thematic analysis also

allows researchers to refine their discovered themes around a specific research question rather than attempting to produce an exhaustive list of all possible themes (Braun & Clarke, 2006). Consequently, I excluded codes were not relevant to a psychosocial understanding of the SCCT framework (e.g. school quality independent of the individual impact it had on students; specific curriculum topics) and thus beyond the scope of this study. See Figure 6 for the SCCT model adapted for these identified themes.

This coding process resulted in two primary codes (exposure to STEM, STEM encouragement) and four secondary codes that represented childhood background influences and three primary codes (hands-on STEM activities, participation in STEM competitions, and classroom STEM help received,) and six secondary codes that represented STEM learning experiences. See Table 1 and Table 2 for these coding tables with definitions, descriptions, and examples.

Table 1. Initial Background Influences Codes

Primary Code	**Secondary Codes**	**Description**	**Examples**
Exposure to STEM	Events (Camps, STEM day) People (Family, siblings, teachers, or friends in STEM majors or careers)	Experiences in which students attended or participated in activities about a STEM topic, major, or career path or interacted with people doing STEM research, studying STEM, or working in STEM careers.	*"My parents… sent me to a summer camp in STEM at Stanford… It was mathematical game theory, so that was like before seventh grade and that was really cool, and I did like it a lot and that's… how I started thinking about maybe math."* *"The influence of my oldest brother because he is doing mechanical engineering at Notre Dame… he helped me in my decision… to go into STEM."*
Encouragement for STEM	Encouragement for General STEM Interest Encouragement for Specific STEM Career	Experiences in which students perceived favorable messages from family, teachers or others regarding their ability to do STEM or their future major or career prospects in STEM.	*"When I was younger [my parents] encouraged me to be involved in science clubs and science projects so I just kind of had exposure to that area a lot. And so, I think that was the only thing I knew and [my parents] were like 'Oh, you should do this.' And I was like, 'Oh, okay, that makes sense.'"* *"I used to like reading a lot, but my dad was like, 'You should do… engineering,' because engineering is money and stuff like that. He actually wanted me to do electrical engineering… They [my parents] played a pretty big role in that."*

Table 2. Initial Early Experiences Codes

Primary Code	**Secondary Codes**	**Description**	**Example**
Hands-on STEM Experiences	Self-Motivated Experiences Parent or Sibling Experiences	Experiences in which the student personally built or interacted with a STEM experiment, project, building, or other construction.	*"We would build stuff… and in school we had this rocket building unit in 5th grade and I thought that was interesting and…cool because we shot out little rockets… That was kind of how I was introduced to it [STEM], and I got really into chemistry later on."* *"When I was little [my family] always did a lot of stuff outside… my brother and I enjoyed… catching bugs and having little plastic peanut butter jar terrariums… [we would] keep them for a while and feed mosquitos to spiders."*
STEM Competitions	Math Competitions Science Competitions	Participation in competitive activities in which the student was tested in math or science topics.	*"I had really good math experiences. We did a pre-competition type thing in third grade and I always… liked it. I was always pretty good at it, and then in fourth grade we had this CML [math] competition. It was… the students in our class taking tests every six weeks and the person who takes the best scores at the end… I got a trophy and… the best scores at the end so I was really happy."* *"I started doing academic UIL competitions in sixth grade. I started competing in the science competition… and I became pretty interested initially in biology just because I feel like at the time that was the most interesting subject to me."*
School Help Received	Help from Parents Help from Teachers	Students received individual help and/or encouragement from a teacher, parent, or sibling on completing school assignments.	*"My mom helped me on [math] homework. She sat me down and told me these are the steps. She taught me how to do long division."* *"In sixth grade… my math teacher… helped me out when I was struggling… He would definitely step in and offer extra help that I don't think he offered other students."*

Exposure to STEM. Some elementary and secondary students never receive exposure to environments or topics that encourage an interest in pursuing a STEM-related topic or career path, and thus never develop intentions to pursue STEM degrees or careers (Xie et al., 2015). For example, many underrepresented minority students do not have relatives or siblings who work in STEM careers (Tai et al., 2006). However, exposure to STEM topics at the K-12 level has been linked to increased intentions to pursue STEM in college and professionally. Of 522 middle school and high school students, those who personally knew a STEM professional were more likely to participate in science-related activities and to have science career interests (Hill, Pettus, & Hedin, 1990). In another study, exposure and engagement in STEM (e.g. visiting science websites or reading science books or magazines) was a small (r = .12) direct predictor of high school students' intentions to major in or pursue a career in science (Lau & Roeser, 2002). A longitudinal study of the effect of participation in a two-week biology and health sciences summer camp for 79 seventh and eighth grade students compared to a control group of students who applied for but were not accepted into the camp found that although science interest decreased for both groups four years later, the decrease was attenuated for participants (Gibson & Chase, 2002). Further, Jarrett and Burnley (2007) found that early STEM exposure, such as visiting museums (along with hands-on STEM experiences), predicted geology students' science interest in college.

Despite the importance of early exposure to STEM, research has typically focused on initiatives at the middle school and high school level, ignoring elementary school students (Dejarnette, 2012). Researchers such as Swift and Watkins (2004) have suggested that it is critical to build problem-solving and critical thinking skills into kindergarten through fourth grade curricula in order to foster long-term interest and academic performance in STEM fields.

Engineering pedagogy researchers are also increasingly identifying the pre-kindergarten through third grade level as critical for exposing students to engineering through hands-on activities, problem solving lessons, and interactive media (Bagiati et al., 2010). Similarly, Russell, Hancock, and McCullough (2007) encouraged the creation of STEM interventions that produce enthusiasm in STEM topics and encouragement of STEM interests regardless of specific program design, and that students be exposed to these initiatives as early as possible (i.e. elementary school).

Encouragement for STEM. Children's daily interactions with parents, teachers, and peers shape, implicitly or explicitly, how the child interprets what science entails, its value, and whether the child can and should pursue it (Aschbacher et al., 2009). Many studies have found that parents' education levels predict their children's math and science achievement and the number of science and math courses taken in secondary school (Chakraverty & Tai, 2013). In particular, parenting approaches may be influential in producing greater STEM achievement or STEM interest in children (Valla & Williams, 2012). For example, middle-class parents are more likely than lower SES parents to communicate a STEM career path as an attainable goal for their children (Archer et al., 2012). Parents may be particularly influential at increasing their child's perceptions of the value of taking advanced STEM coursework. In an intervention in which parents received information and access to a website on STEM careers, their children took almost a semester more on average of math and science courses during their last two years of high school than the control group (Harackiewicz et al., 2012).

Parental involvement in children's math education plays a strong role in STEM achievement. In a longitudinal study of over 12,000 students from eighth to twelfth grade, eighth graders who talked to their parents about school had higher math achievement scores, although

that association weakened upon reaching high school (Muller, 1998). Higher levels of parental education and family income were also related to higher math achievement scores in eighth and tenth grade (Muller, 1998). In an international study of 34 countries, parental education level predicted students' math achievement, even when the child's mathematics ability was controlled (Schiller et al., 2002). In a qualitative study of 158 fifth grade students and their mothers, mothers who had higher math education and greater self-confidence in math were better at teaching their children new math content (Hyde et al., 2006). Together, these findings imply that children whose parents have less involvement in their school and less formal education will have weaker math preparation in elementary and middle school, potentially impacting students' preparedness for higher level STEM coursework.

Hands-on STEM activities. The importance of hands-on activities for STEM students may reflect vocational interest types and identity as a STEM student. *The RIASEC interest type inventory*, or Holland Occupational Themes, is a vocational preference inventory that consists of six core types, representing various preferences for work requirements and activities (Holland, 1997). Two interest types in particular – Realistic and Investigative – may be especially relevant for STEM-specific careers (Lapan, Boggs, & Morrill, 1989). The Investigative type represents a preference for problem-solving tasks, understanding information, and showing curiosity; the Realistic type represents a preference for hands-on activities, including manual manipulation and a concrete approach to problem solving (Holland, 1997). In this model, career interests are hypothesized to be the result of students' self-efficacy toward meeting the standards and tasks implied by various vocational preferences and their inherent interest in these preferences (Betz & Hackett, 1981). In terms of specific STEM fields, biology has been linked to the Realistic interest and chemistry to the Investigative interest (Blankenburg et al., 2016); engineering has

been studied with respect to both Realistic and Investigative preferences (Bruch & Krieshok, 1981).

STEM identity is the extent to which students believe they are competent, high-performing, and recognized by others as proficient in one or more STEM fields (Carlone & Johnson, 2007). It may interact with or be the result of a preference for hands-on activities and has also been described as one's belief or self-concept as having one or more STEM interests (Johnson, Brown, Carlone, & Cuevas, 2011). Identity is a subjective belief that is impacted by one's sense of awareness that others recognizes that individual's self-concept (Erikson, 1994). In a study by Capobianco, French, and Diefes-Du (2012), 184 first through fifth grade students enrolled in a hands-on intensive six-week engineering curriculum were able to reliably articulate their engineering identity through valid responses on an engineering identity measure. In the identity development model (Marcia, 1993), people who have not only explored their own goals (the traditional concept of identity) but subsequently made an intentional psychological commitment to their goals, perspectives, and perceptions have the highest general well-being and decision-making ability. Personal identity is developed through close interpersonal interactions and experiences, which then interacts with cultural and demographic norms and experiences, influencing one's social identity (Cote & Levine, 2014).

A modern understanding of science remains largely influenced by the experiences, cognitions, and biases of White, middle-class males (Aschbacher et al., 2009). As a result, many underrepresented minorities and female students struggle to reconcile their personal and social identity with their STEM identity, especially as it pertains to *identity threat*, in which students believe their social identities will be devalued or disregarded in STEM settings (Murphy et al., 2007). Academic norms make science inherently less accessible to students from other

backgrounds and requires students to navigate multiple identities that may conflict with one another. These struggles begin as early as elementary school and extend into college (Aikenhead & Jegede, 1999). Underrepresented minority students in particular may have different "funds of knowledge," or knowledge and skills based on their background experiences and upbringing that they bring into the classroom (Moll et al., 1992). In elementary and middle school science classes, students must learn not only the class's content but also a new way of conceptualizing science. For example, students may have social and cultural identities that foster a poetic or religious reverence for natural phenomena that comes into conflict with a more traditional mathematical or reductionist perspective of science; Aikenhead & Jegede, 1999). An early disconnect between personal and social identity and mainstream classroom culture can have negative ramifications for students' STEM identity in the future (Barton & Tan, 2009). Conversely, students who have been able to reconcile their own identity with their STEM identity might be more likely to develop and maintain strong STEM interests.

STEM competitions. Psychological constructs relevant to participating in math or science competitions may reflect motivation and mindset theories. *Motivation* drives one's energy and effort to learn, work, and achieve, impacting the behaviors that reflect these drives (Eccles & Wigfield, 2002). Motivation can be defined as either a mastery orientation or performance orientation toward completing tasks in a certain domain (Ames & Archer, 1988). *Academic motivation* refers to how students frame their goals in academic activities and is a strong influence on students' behavior in school and their enjoyment of school (Martin, 2002). Students whose goal is to their increase competence or knowledge when performing a task represent a learning focus; students whose goal is to meet external standards for competence and avoid external perceptions of failing at a task represent a performance focus (Nicholls, 1989).

Learning-focused students are more likely to respond to challenges (such as difficult STEM topics) adaptively by framing them as opportunities to increase their effort or change strategies; students with a performance focus are more likely to focus on outperforming others (Martin, 2002). Motivational sources of influence can also be described as *intrinsic* (internally driven) or *extrinsic* (driven by outside pressures or incentives). STEM competitions are a source of extrinsic motivation, meaning that some students who like and seek out competitions might be driven to take actions they believe will make them more likely to do well in the competition rather than to frame the competition as an opportunity to learn more about a topic.

Mindset refers to one's beliefs about the nature of intelligence (Dweck, 1999). Although mindset may interact with many of the themes in this study (e.g. STEM identity, classroom STEM help received), here it is conceptualized as most relevant in contributing to understanding how students approach competitive situations. Students with a *fixed mindset* believe that their intelligence and abilities are fixed or permanent; those with a *growth mindset* believe that their intelligence and abilities can grow from persistence (Dweck & Leggett, 1988). Differences between the two types of mindsets are typically not seen until a student faces challenges or setbacks, which in school settings often does not occur until middle school (ages 12 or 13; Dweck, 2008). Mindset can impact how students respond to praise (or criticism) based on others treating the student' behavior as either the result of innate talent or their process or effort. Multiple studies have shown that students persist in difficult tasks for longer, ultimately have greater achievement levels, and maintain greater levels of motivation if they receive a message that improvement is possible and that feeling challenged by their assignment is normal (Dweck, 2008).

Mindset may be particularly important regarding STEM topics, especially math. Students tend to have a fixed mindset for math ability more so than other school skills (Dweck, 2008). A longitudinal study by Blackwell, Trzesniewski, and Dweck (2007) found that of two groups of seventh grade students who originally had the same math achievement levels, students with a growth mindset had higher math achievement two years later. A computer-based math game that promoted a growth mindset for elementary school students learning fractions found significant differences in how long the children persisted in voluntarily playing the game, with the strongest impact on the persistence of the children with the weakest fraction skills (O'Rourke et al., 2014). A study of the impact of a mindset intervention on fifth-grade students instructed to complete a series of progressively more difficult matrix (visual geometry pattern completion) problems found that the growth mindset group persisted longer after failure, enjoyed the task more, and had higher achievement levels (Mueller & Dweck, 1998). Together, both motivational and mindset theories may contribute to an explanation of how different students approach competitive environments in both adaptive and maladaptive ways.

Classroom STEM help from teachers. Schools provide a climate and set of social norms, and this environment influences students' interactions with their teachers and each other, their academic achievement expectations, and their overall behavior at school. These factors, even if they seem subtle, can have long-term repercussions on motivation and academic outcomes (Eamon, 2005). In particular, teacher support predicts many academic outcomes, particularly in developing positive classroom environments and providing students attention and feedback that is sensitive and responsive to students' needs (Hamre & Pianta, 2005). Classroom *social adjustment* refers to liking and engaging with the school environment and exhibiting self-control and emotional regulation in the classroom. It is strongly influenced by teachers (Birch &

Ladd, 1997). For example, a study of 206 kindergarten students found that students who had close relationships with their teachers had higher social adjustment and academic performance (Birch & Ladd, 1997). Social adjustment early in elementary school is critical and can predict important student psychological and academic outcomes years later (Entwisle & Hayduk, 1988). In a longitudinal study of students tracked from first through eighth grade, negative indicators of social adjustment in first grade were especially salient, predicting greater conflict, lower academic achievement, and greater behavioral problems through the eighth grade, especially for boys (Hamre & Pianta, 2005). Strong teacher-child relationships can lead to teachers spending more time encouraging the student than students with whom they have weaker relationships (Hamre & Pianta, 2005). Additionally, students who are able to form positive interactions with a school-based mentor in face of poor family dynamics may be able to find social support as a protective factor for academic achievement when they could not find it within their own family (Noam et al., 2001).

Teachers may be particularly vital for encouraging high math achievement. Unlike reading (the other critical academic skill learned in elementary school) math skill depends on the child's school and teachers to a greater extent than his or her family environment, and skill is lost to a greater extent over the summer months than with reading (Borman & Overman, 2004). A study of 1,163 upper elementary school students found that students' perceptions of having a positive but challenging classroom environment predicted higher math self-efficacy, which in turn predicted higher math achievement (Fast et al., 2010). A longitudinal study of students transitioning from sixth grade (which was elementary school in this study) to seventh grade (junior high school) found that students reported weaker relationships with their math teachers, fewer opportunities to collaborate in the classroom, and less autonomy in approaching math

problems in seventh grade as compared to sixth grade (Feldlaufer et al., 1988). A study of 317 seventh and eighth grade students found that student's perceived support from their math teachers explained significant variance in their self-efficacy, liking of school, sense of belonging, and academic effort (Sakiz et al., 2012). A longitudinal study of eighth grade students tracked until the twelfth grade found that the impact of perceptions of teacher support in school was a weak predictor of student math achievement overall, but a stronger predictor for low performing students in particular (Muller, 2001), supporting the idea that teacher support may be a protective factor for students at greater risk of academic difficulties.

Biodata Item Development

When constructing the biodata measure, items were designed to capture relevant constructs and themes to then incorporate into the SCCT model for testing. For item content, I used an inductive approach (Hinkin, 1995), using narratives generated by interviewees to produce items that were similar to the background influences or formative experiences the interviewees described. Based on the guidelines for item development by Lent and Brown (2006), I designed items that were strongly contextualized in the STEM domain exclusively (with the exception of the classroom help theme, as interviewees were primarily in classes during their childhood in which teachers taught all subjects), comprehensive in attempting to capture all relevant content the interviewees provided, and compatible between the predictor and criterion using SCCT as a framework for predicted relationships. Similar to Mumford, Costanza, and Connelly's (1996) study which described generating 10-15 proposed items per construct, I developed 10-15 items for each of the five primary codes. Items reflected attributions that students make after the fact, with participants assigning meaning to events that took place in elementary and middle school.

Assessment of the measure's content validity. The 60 biodata items I developed were divided between background influences (two themes) and learning experiences (three themes). The original items are reported in Appendix A. I included all items on a Qualtrics survey I administered to undergraduate research assistants in the Adult Skills and Knowledge Lab (*n* = 12). The survey had two primary sections. To ensure my items met Tourangeau, Rips, and Rasinski's (2000) item development guidelines, in the first section of the survey I listed every item and asked respondents to comment on any item that was unclear or confusing so that I could identify any items that contained unfamiliar words or ambiguous terminology, that used complex language when more concise language could be used, or that appeared to be assessing multiple concepts or constructs within a single question. On the next section of the survey, I assessed the item's content validity in capturing the theme or construct I originally intended. Participants were instructed to sort each item into one of the five themes, indicate if it seemed to fit into more than one theme, or indicate if it did not appear to fit into any theme. Through providing the final two sorting options as well as a participant free response section to further understand participants' individual sorting decisions, my goal was to counteract the tendency for qualitative ranking methods to require respondents to be passive and restricted to pre-determined categories rather than allowed to express their subjective cognitions and experiences sorting the measures (see Watts & Stenner, 2005).

Results from the assessment. For both sections, I established a threshold of acceptable content validity as items that 80% or more of participants (i.e. ten or more of the participants) reported without issues in wording (the first section) and also sorted into the same category (the second section). If items did not meet this threshold on both parts of the survey, the item was reviewed for further refinement. In the first section of the survey, 35 items (58%) were marked

by 80% or more participants as being clear to understand and without any comments by participants. In the second section, 25 items (42%) were sorted by 80% or more participants into the same category. Combined, twelve items met the thresholds of both sections (i.e. they were identified as being clearly written, had no comments by participants, and were sorted by 80% or more participants into a single category). These 12 items were included without altering in the updated version of the survey. The remaining 48 items were reviewed for further improvement.

Eleven items met the threshold of both sections, but one or more respondents had written comments about the item. I reviewed these items and re-worded them based on respondent suggestions. Additionally, I generated four additional items in response to reviewing comments from these items based on comments that suggested clarifying the item between two possible interpretations. I created separate items to explicitly address each interpretation. For example, "How comfortable did you feel approaching your teacher with class questions?" became 1) "How comfortable did you feel approaching your teacher with class questions after class?" and 2) "How comfortable did you feel asking your teacher questions during class?"

Next, I examined the items that did not meet the 80% sorting threshold ($n = 37$) and their associated comments. One frequent comment that was also replicated in variability in sorting task responses showed that students struggled to identify whether receiving help from parents fit into the "Receiving Help in School Settings" theme. Therefore, I reconceptualized this theme as "Receiving Help on School Assignments" and defined help from teachers and help from parents as two distinct sub-themes. This process resulted in re-writing three items to clarify that the item was referring to school assignments, classifying two items into this category without alteration, and dividing another into two items.

Next, I identified items for which participants struggled to differentiate between the two background influences themes ("Exposure to STEM" and "Encouragement for STEM"). Respondents noted in their comments that exposure could in some circumstances seem to be encouragement. Instead, respondents made a distinction between verbal encouragement and whether the student had been provided with various STEM-related resources or opportunities. As a result, I re-classified the original two background influences themes to 1) "Exposure or Encouragement in STEM" and 2) being "Provided STEM Resources." I then reviewed all items sorted into either category. I added items that referred to being provided money or other resources to pursue STEM into the second theme and all other items that respondents originally sorted into the "Exposure to STEM" or "Encouragement for STEM" themes into the first factor.

Then I reviewed all remaining items and comments to identify items that could be re-written to better fit into the most-commonly sorted theme for each item. For example, an item referring to "How often did you participate in special science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?" was sorted by most participants into the "STEM Exposure" category but by several participants into the "STEM Competitions" category; therefore, I altered the item to "How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?" Fifteen items were re-written to more precisely fit into a specific theme, including two items that were each divided into two items.

Finally, four items remained that participants had sorted into multiple categories. I reviewed these items and determined that they all reflected a general theme of the hypothetical respondent being proactive or exhibiting voluntary behavior. For example, items included "How likely were you to ask others for STEM-related gifts for your birthday or other holiday?" and

"How likely were you to seek out information on STEM events you wanted to attend?" As a result, I classified these items into a new "Proactive Behavior" theme. After completing this revision process, items now were classified as belonging to one of six themes. See Table 3 and Table 4 for the revised codes.

Table 3. Revised Background Influences Codes

Primary Code	**Secondary Codes**	**Description**	**Examples**
1) Exposure and Encouragement for STEM	Exposure to Events and People	Experiences in which students attended or participated in activities about a STEM topic, interacted with people studying or working in STEM, or perceived favorable messages from others regarding their ability to work or study in STEM.	*"The influence of my oldest brother because he is doing mechanical engineering at Notre Dame… he helped me in my decision… to go into STEM."*
			"When I was younger [my parents] encouraged me to be involved in science clubs and science projects so I just kind of had exposure to that area a lot. And so, I think that was the only thing I knew and [my parents] were like 'Oh, you should do this.' And I was like, 'Oh, okay, that makes sense.'"
	Encouragement for STEM Interest or Careers		*"I used to like reading a lot, but my dad was like, 'You should do… engineering,' because engineering is money and stuff like that. He actually wanted me to do electrical engineering… They [my parents] played a pretty big role in that."*
2) Being Provided STEM Resources	Financial Resources	Experiences in which students were provided resources, including materials and STEM experiences or activities for which their parents or school paid.	*"My parents… sent me to a summer camp in STEM at Stanford… It was mathematical game theory, so that was like before seventh grade and that was really cool, and I did like it a lot and that's… how I started thinking about maybe math."*
	Other Resources		*"My teachers usually gave me a lot of freedom and just resources to learn more… My gifted teacher would give me space magazines and stuff like that, like astronomy magazines. My regular science teachers would tell me books that I could check out from the library that had topics that I liked and stuff like that or would give me a little bit more freedom on projects that we could do."*

Table 4. Revised Early Experiences Codes

Primary Code	Secondary Codes	Description	Examples
3) Having Hands-on STEM Experiences	Self-Motivated Experiences	Experiences in which the student personally built or interacted with a STEM experiment, project, building, or other construction tool.	*"We would build stuff… and in school we had this rocket building unit in 5th grade and I thought that was interesting and…cool because we shot out little rockets… That was kind of how I was introduced to it [STEM], and I got really into chemistry later on."*
	Parent or Sibling Experiences		*"When I was little [my family] always did a lot of stuff outside… my brother and I enjoyed… catching bugs and having little plastic peanut butter jar terrariums… [we would] keep them for a while and feed mosquitos to spiders."*
4) Participating in STEM Competitions	Math Competitions	Experiences in which the student engaged in competitive activities and was tested in math or science topics.	*"I had really good math experiences. We did a pre-competition type thing in third grade and I always… liked it. I was always pretty good at it, and then in fourth grade we had this CML [math] competition. It was… the students in our class taking tests every six weeks and the person who takes the best scores at the end… I got a trophy and… the best scores at the end so I was really happy."*
	Science Competitions		*"I started doing academic UIL competitions in sixth grade. I started competing in the science competition… and I became pretty interested initially in biology just because I feel like at the time that was the most interesting subject to me."*
5) Receiving Help on School Assignments	Help from Parents	Experiences in which the student received individual help from a teacher, parent, or sibling on completing school assignments or projects.	*"My mom helped me on [math] homework. She sat me down and told me these are the steps. She taught me how to do long division."*
	Help from Teachers		*"In sixth grade… my math teacher… helped me out when I was struggling… He would definitely step in and offer extra help that I don't think he offered other students."*

Primary Code	Secondary Codes	Description	Examples
6) Proactive or Voluntary STEM Behaviors	Seeking Resources Voluntary Activities	Experiences in which students proactively sought out information, found resources, or spent time doing STEM activities that were not mandatory	*"If I wanted books or toys or something that was related to science, [my parents] would give it to me for birthday."* *"They [the school] gave us the opportunity to go to this space museum in our town and they were holding a rocket launch, so we went to it. That was just something I was invited to go to, and I was like yeah sure, that would be something nice to try."*

Because many items (n = 21) now fit into the new "Exposure or Encouragement in STEM" theme, three themes contained fewer than ten items. To meet my goal of having at least ten items per theme, I generated more items based on the original interview data and comments from respondents to ensure that each factor contained at least ten items. See Figure 2 for the revised model. The full 72-item measure is included in Appendix B.

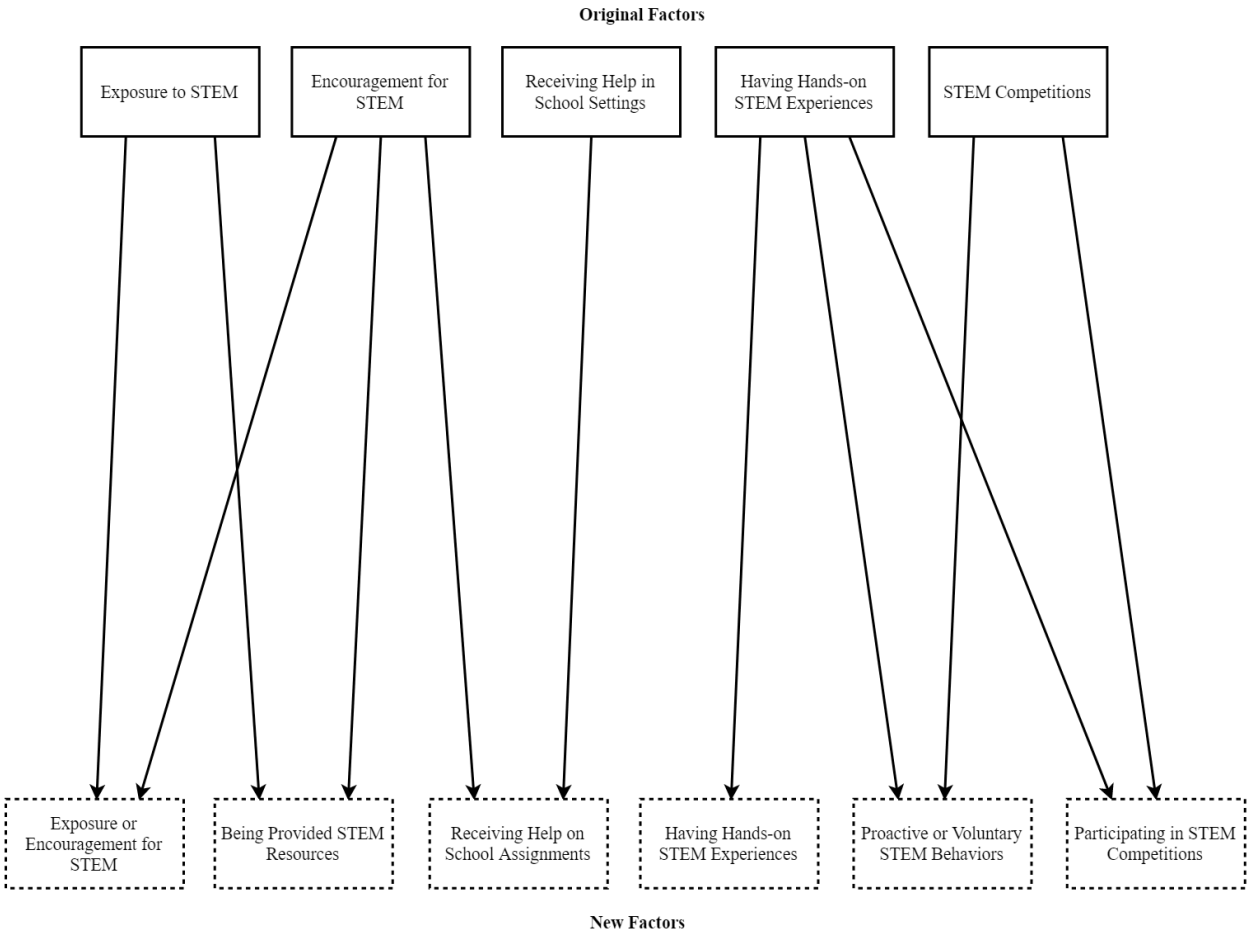

Figure 2. Adapted biodata factor model after pilot testing

Pilot Testing the Measure

I administered the updated measure to undergraduate research assistants (N = 11), with items being randomly ordered. I also asked participants to again report comments or suggestions on the items. The mean time to complete the measure was ten minutes and 58 seconds. Based on participant comments, I updated two items. For the 10-item "Competitions" factor, Cronbach's alpha was .836. For the 21-item "Encouragement" factor, two items could be removed to substantially increase alpha. One item was removed, and the other was retained but re-written for clarity. Cronbach's alpha was .934. To reduce the items in this factor to ten correspond with the

number of items in the other factors, I examined item content and also identified items with the lowest correct item-total correlations to guide my selection process (a sample size of 11 was too small to solely rely on a quantitative measure to identify items to be removed). For the 10-item "Hands On" factor, Cronbach's alpha was .911. For the 10-item "Help" factor, Cronbach's alpha was .903. For the 10-item "Proactive" factor, Cronbach's alpha was .677. Two items could be removed in this factor to substantially increase alpha. One item had a narrow range of responses, which I retained in the measure due to the possibility of the small sample size artificially restricting the range. The other item was re-written to ensure the item captured the theme as a behavioral rather than attitudinal construct. For the 10-item "Provided STEM Resources" factor, Cronbach's alpha was .848. Descriptive statistics are reported in Table 5. The 60-item measure is included in Appendix D.

Table 5. Original Biodata Factors

	Factor	***α***	***n* items**
1	STEM Competitions	.914	10
2	Exposure to STEM	.881	10
3	Hands On STEM Activities	.846	9
4	Help for STEM	803	7
5	Proactive Behavior	.811	10
6	Provided STEM Resources	.882	10

Summary

In this section, I provided a description of the process of developing a biodata measure of STEM formative experience. This process started with qualitative data analysis using thematic analysis to develop a factor structure of five distinct themes and ten themes, based on interview data STEM students provided in a previous study. After initial assessment of the 60-item

measure and subsequent pilot testing on undergraduate students, I clarified, divided and removed items, and then ultimately sorted them into a new six-factor data structure. With initial pilot testing complete, the measure was now refined enough to be tested and validated on a larger sample for the first time.

CHAPTER 4: CURRENT RESEARCH

This research is guided by social cognitive career theory (SCCT), a framework describing how students develop and build on academic and career interests, make choices regarding these interests, and eventually succeed or fail as a result of these choices (Lent et al., 1994). I examined early background influences and learning experiences and the relevance of these constructs on students' subsequent STEM and other academic choices and behaviors using the measure described in the previous chapter and further refined over the course of the following studies.

Research Summary

This research comprised two studies: Study 1 was designed to validate the previously described biodata measure; Study 2 was designed to determine whether this measure fit the relationships predicted by the SCCT model (see Figure 3 on page 48 for the hypothesized model). In both studies I used Rice students as participants, although inclusion criteria differed between the two studies.

Study 1

Study 1 used the refined biodata measure after the pilot study (see Appendix D) to establish convergent and discriminant validity with related psychological constructs. Rice students of any year who qualified (based on their high school records) for Rice's STEM summer bridge program designed to increase STEM retention were eligible to participate in Study 1. Students did not need to be current STEM majors to participate.

To examine convergent and discriminant validity, I used several established scales. The first was the Big Five personality traits (agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience). Four of the five personality traits in the five factor

model, which describes five broad, global dimensions of an individual's personality (McCrae & John, 1992), have consistently demonstrated correlations with various occupational interests (i.e. all five-factor dimensions except neuroticism correlate with occupational interests operationalized as RIASEC vocational interest scores; Ozer & Benet-Martínez, 2006). In particular, a meta-analysis by Barrick and Mount (1991) found a medium correlation between the openness to experience dimension and the investigative vocational interest; therefore, this factor was assessed as a source of convergent validity in this study.

Hypothesis 1: The biodata measure will demonstrate moderate (approximately $r = .30$) convergent validity with openness to experience.

Conversely, I expected agreeableness to be independent of biodata measure scores and thus provide evidence of discriminant validity. Agreeableness has been linked to interest in socially-oriented occupations; however, traditional STEM career paths do not tend to correspond with high social interests (students with high interests in both social occupations and STEM topics tend to pursue the health sciences, which are not traditionally defined as STEM fields; Su & Rounds, 2015).

Hypothesis 2: The biodata measure will demonstrate discriminant validity with agreeableness.

Next, I expected proactivity to show convergent validity with at least the "Proactive Behavior" factor developed after initial item assessment and pilot testing. Proactivity reflects the concept that individuals are not passive actors responding to situations and circumstances but part of a dynamic and dual process in which individuals also interact with and change their environments (Bateman & Crant, 1993). Students may proactively influence their own situations by reframing their thoughts and perceptions of their environment, changing their social

environment by unintentionally evoking responses from others, by intentionally selecting specific situations in which to participate, and by manipulating their interpersonal circumstances (Buss, 1987). Proactivity may be linked through other components of STEM formative experiences in this biodata measure, such as items that refer to students participating in voluntary STEM competitions or attending voluntary science demonstrations.

Hypothesis 3: The "Proactive Behavior" biodata factor will demonstrate moderate convergent validity with proactivity.

Finally, addressing broader social factors, I expected students' experiences in elementary school, including their school quality, teacher helpfulness, and the availability of books at home, to show convergent validity with biodata factors such as "Encouragement and Exposure to STEM" and "Receiving Help in School Settings." As previously discussed in Chapter 2, school quality correlates with students' access to STEM equipment and enrichment opportunities, and higher resourced elementary and middle schools are more able to provide their students opportunities for exposure to STEM topics or teaching experiences than students from lower resourced schools. Students from non-underrepresented minority backgrounds may also encounter fewer barriers through their interactions with teachers, regardless of their school quality, as also discussed in Chapter 2. Children's access to books at home is also well supported in the literature as being integral to children's developing literacy skills and reading interest (Neuman, 1999).

Hypothesis 4: The "Encouragement and Exposure to STEM" and "Receiving Help in School Settings" factors will demonstrate moderate convergent validity with school quality, teacher helpfulness, and book availability.

Finally, the number of elementary schools students attended might have non-existent or negative relationships with the biodata factors, based on the research on the importance of a stable elementary school experience on long-term academic success (e.g. Sandstrom & Huerta, 2013).

Hypothesis 5: The biodata measure will demonstrate discriminant validity with the number of elementary schools that students attended.

The study initially used confirmatory factor analysis to examine whether the biodata items fit into the theoretically developed themes I developed based on initial assessment and pilot testing.

Hypothesis 6: The data will show evidence of six distinct factors (Exposure and Encouragement for STEM, Being Provided STEM Resources, Having Hands-on STEM Experiences, Participating in STEM Competitions, Receiving Help on School Assignments, and Proactive or Voluntary STEM Behaviors), with individual items loading onto the *a priori* anticipated factors.

However, because fit of this *a priori* model was relatively poor, I conducted an exploratory factor analysis and refined the model to comprise seven factors, which I tested in Study 2.

Study 2

Study 2 administered an updated version of the biodata measure (the post-Study 1 measure; see Appendix I), along with measures of STEM interest, career interest, psychological outcomes, and objective academic data to develop a structural equation model and determine whether the data followed the paths predicted by the SCCT model. Students in this sample were

freshman students of any major taking any undergraduate class that allowed or required participation in the SONA subject pool See Figure 3 for the full model tested.

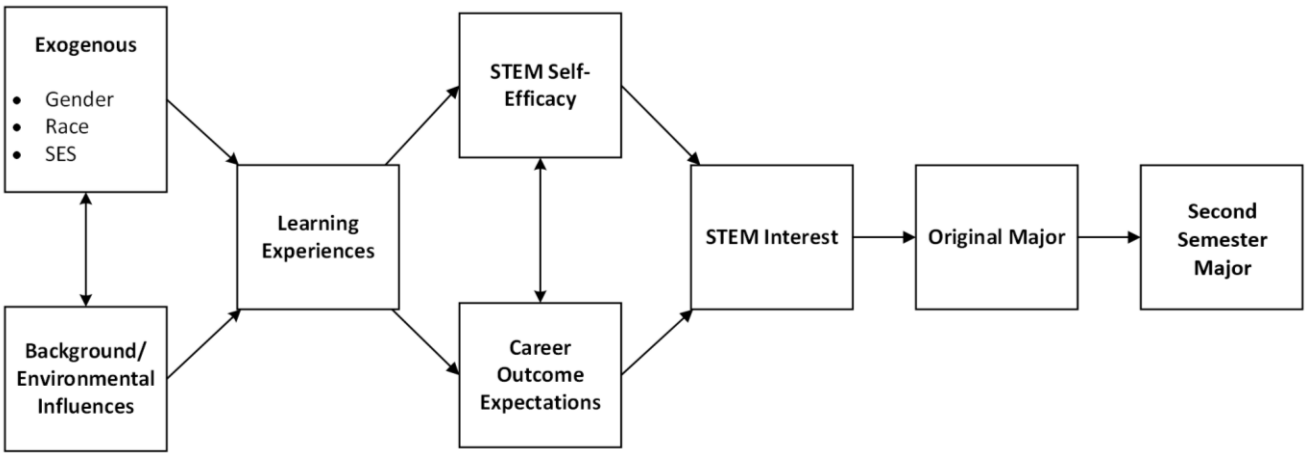

Figure 3. SCCT model, adapted for a STEM context, to be tested in Study 2

For this study, I view intended or originally declared college major as students' choice goal. Although incoming students are not required to declare a major upon matriculation, they do declare a school, and one might anticipate that students will also feel comfortable stating their original major interest on an anonymous survey in a way that they did not feel comfortable declaring officially to Rice (and indeed, all students did report an initially preferred major on the survey). These initial major plans might reflect certain expectations or interests they would have liked to explore in their first semester classes. Students also tend to underestimate the uncertainty regarding whether they will remain in their original major (Stinebrickner & Stinebrickner, 2014), meaning that initial college major is truly a "starting point" in the path of students' academic decisions during college. Entering freshmen students, especially those with less exposure to the

college process, often struggle to link their initial major to their career goals and do not actively strategize on how to use it to explore or prepare for a career path (Clark, 2005).

I viewed students' expectations of their future major at the end of their second semester as the most distal outcome of interest in this study and the choice action, based on the SCCT model. I expected there to be a difference for many students between their initial major and their intended major as they approach the end of their freshman year, because a almost half of college students switch majors (a national longitudinal data set of approximately 9,000 students found that 43% of students switched their major at least once; Astorne-Figari & Speer, 2019). Further, some challenges within a chosen major may not occur until students' second semester, when they must interpret their academic performance from the previous semester and make decisions as a result of their perceptions of their first-semester college experience (Clark, 2005).

Research Question 1: Which background influence themes predict students' second-semester major?

Research Question 2: Which formative experience themes predict students' second-semester major?

Research Question 3: How well do the data obtained from the surveys and students' academic records fit the proposed model based on the SCCT?

CHAPTER 5: STUDY 1

Method

Study 1 involved collecting biodata and other survey measures to examine evidence for the proposed biodata factor structure using factor analysis, as well as examine convergent and discriminant validity with other measures.

Participants

Participants were 154 sophomores, juniors, or seniors who qualified for or participated in the Rice Emerging Scholars STEM summer bridge program at Rice. An *a priori* power analysis of the sample size necessary for a correlation model to detect a medium effect size (r = 0.30; β = .80, α = .05) produced a required sample of 132 students. Participants were 41.3% Hispanic or Latino (n = 59), 19.6% Black or African American (n = 28), 19.6% White (n = 28), 11.9% Asian American (n = 17), and 7.7% multiracial or other (n = 11). Race data were unavailable for 11 students. Participants were 64.3% female (n = 99).

Measures

Biodata questionnaire. Sample items from the revised version of the biodata measure after pilot testing the measure include two background influence factors, with items such as "How often did you talk to siblings or cousins who were studying STEM in high school or college about STEM topics?"(Being Exposed or Encouraged for STEM) and "How likely were your parents to provide you with the materials to work on STEM-related projects?" (Being Provided STEM Resources). Items for the four formative experiences factors include "How likely were you to get bored of working on mandatory hands-on STEM activities? (Reversed Coded)" (Having Hands-on STEM Experiences), "How likely were you to participate in math competitions that were voluntary?" (Participating in STEM Competitions), "How capable were

your parents of helping you on a math assignment if you needed help?" (Receiving Help on School Assignments), and "How likely were you to choose to attend or participate in STEM events that were voluntary?" (Proactive or Voluntary STEM Activities). For each section, students were shown the prompt: "When you were elementary school age (11 and younger)..." As with many biodata studies (e.g. Mumford, Costanza, & Connelly, 1996), the questionnaire is on a 5-point Likert scale format, representing the degree or frequency to which each item was expressed. See Appendix D for the revised 60-item measure. The internal consistency of the scales are provided using Cronbach's alpha (Cronbach, 1951) when available.

Other scales. To establish convergent and discriminant validity, I first explored the openness to experience and agreeableness personality traits (McCrae and John, 1992). Each personality trait was assessed with a brief 4-item scale developed and validated by Donnellan, Oswald, Baird, and Lucas (2006). Responses are scored on a 5-point Likert scale ranging from *1 = Very Like Me* to *5 = Very Unlike Me.* For openness to experience, items include: "Have a vivid imagination" and "Am not interested in abstract ideas (RC)." Cronbach's alpha was .65 in a sample of first-year undergraduates (Donnellan et al., 2006). For agreeableness, items include: "Sympathize with others' feelings" and "Am not really interested in others (RC)." Cronbach's alpha was .70 on the same sample.

STEM identity. A measure of STEM identity was used to establish convergent validity with the biodata measure. Identity was measured using a ten-item, five-point Likert scale measure ranging from *1 = Strongly Disagree* to *5 = Strongly Agree* adapted from Rittmayer and Beier's (2008) STEM identity scale. Example items included: "I have always done well in STEM classes" and "I enjoy my STEM courses more than other courses I have taken."

Proactivity. A ten-item measure of proactive behavior by Seibert et al. (1999) was used to measure proactivity. Items included: “I am constantly on the lookout for new ways to improve my life” and “I excel at identifying opportunities.” Cronbach’s alpha in the Seibert et al. (1999) study was .86.

Educational quality. I used three measures of students’ elementary school experiences. First was an eight-item measure of students’ school and teacher quality. Items were adapted from Cronin and Taylor (1992) and Parasuraman et al. (1988) to refer to elementary school experiences, and students were instructed to respond based on the elementary school they attended the longest. Responses were ranked from *1 = Very Untrue* to *5 = Very True*. Example items were: “My elementary school had up-to-date equipment” and “I could trust my elementary school teachers.” The next two measures comprised single items. The first was “How many books were in your home that you had access to growing up?” Responses ranged from *1 = Less than one bookshelf* to *5 = More than two bookcases*. The second item addressed the number of elementary schools attended in kindergarten through fifth grade. Options ranged from *1* to *6 or more*, or that the student was homeschooled. Both of these items were adapted from a study of students’ educational opportunities (Woessmann, 2004).

Objective measures. Student math SAT and ACT scores were obtained from student applications. On the survey, participants also reported which STEM AP classes they took in high school. I expected both math standardized test scores and the number of AP STEM classes taken in high school to show convergent validity with the biodata measure.

Addressing common method bias. Common method bias is a source of measurement error that results from the same measurement instruments and sources being used to draw statistical conclusions (Campbell & Fiske, 1959). Because common methods bias may contribute

to observed relationships between variables (positively or negatively), correlations may not be due to true variance among constructs of interest, which challenges the validity of any relationships discovered (Bagozzi et al., 1991). I minimized common method variance in several ways, using the procedural solutions that Lent and Brown (2006) and Podsakoff et al. (2003) proposed in guiding survey design and administration when feasible. First, I separated the items for various constructs on different pages of the survey form, to reduce participants' tendency to be self-consistent in ratings. Second**,** although I did not expect social desirability to be a significant concern in influencing participants' responses to these measures, in the instructions to participants I advised them that there were no incorrect answers and that no outside parties would ever see their survey response data before it is anonymized**.** Third, this study also used objective data in the form of math standardized exam scores (based on university records) and STEM AP classes (based on self-report), which provided additional and objective sources of data. Finally, I used a STEM identity scale from a previous survey, providing a source of data from a different time period than this data collection period.

Procedure

I administered the biodata measure, along with the other measures designed to capture convergent and discriminant validity, in a Qualtrics survey in Spring 2020. Items were added to an existing survey that students complete three times a year. Students received an email at the beginning of January with a link to the Qualtrics survey. Non-respondents received two more reminder emails over the following two weeks. Because this survey was part of an ongoing NSF-funded research grant, students were paid $20 at the end of the spring semester for completing this survey. Confirmatory and exploratory factor analyses were conducted in R using the *lavaan* and *psych* packages.

Results

Of the 154 students who took the survey, six did not respond to the complete survey but did complete the biodata measure (which was the first section of the survey), meaning that n = 154 for the biodata measure and n = 150 for the other measures. There were no outliers found in these data based on time to complete the survey or irregular individual survey responses. Participant demographic data are included in Table 6.

Table 6. Study 1 Participant Demographic Data

	Gender			
Race	Female	Male	Total *n*	Total as Percentage
Asian	14	3	17	11.9%
Black or African American	20	8	28	19.6%
Hispanic or Latino	34	25	59	41.3%
Multiracial or Other	6	5	11	7.7%
White or Caucasian	17	11	28	19.6%
Total	**91**	**52**	**143**	**100%**

Note. Demographic information by race was unavailable for 11 participants.

I first examined the internal reliability of the scales and removed items that did not significantly contribute to the reliability, resulting in a 56-item measure to be used for further analysis. Factor loadings of the modified scale are listed in Table 7; reliability and number of items for each factor in the modified scale are listed in Table 8.

Confirmatory Factor Analysis

Using the refined version of the scale, I ran a confirmatory factor analysis to determine whether the items loaded onto the expected six factors and appeared to capture the distinct theoretical constructs I used when designing items. The originally proposed six-factor model did not show acceptable fit ($\chi^2(1310) = 3056.87$, *CFI* = .663, *TLI* = .645, *RMSEA* = 0.094).

However, this model was still a better fit for the data than a one-factor model ($\chi^2(325) = 3897.08$, *CFI* = .504, *TLI* = .484, *RMSEA* = 0.114; $\Delta\chi^2(15) = 840.21$, $p < .001$), suggesting that a factor structure did exist in these data.

Exploratory Factor Analysis

Because the *a priori* hypothesized six-factor structure did not fit the data well, meaning Hypothesis 6 was not supported, I then conducted an exploratory factor analysis on these data. I used all the original items ($n = 60$) in this analysis. Parallel analysis suggested that there were as many as seven factors within the data. A review of the scree plot showed that a fit of three to seven factors might be appropriate. See Figure 4 for the scree plot.

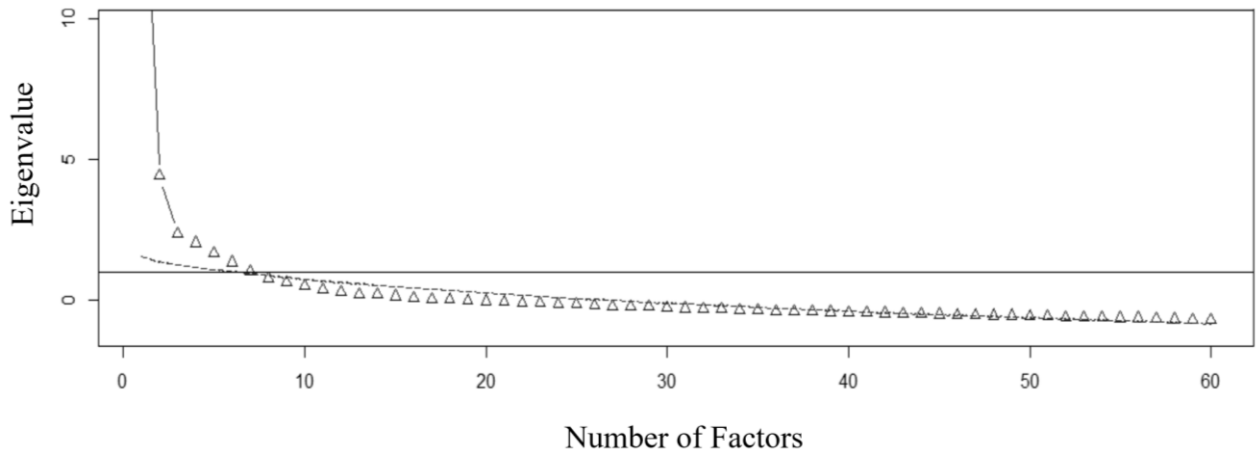

Figure 4. Scree plot of exploratory factor analysis in Study 1

After reviewing the factor loadings (from three to seven factors) for each model, the seven-factor model provided the best fit (*CFI* = 0.884, *RMSEA* = 0.048). The *CFI* approaches the acceptable level of 0.90 (Hu & Bentler, 1999). I used a 0.400 criterion as an acceptable fit for factor loadings on social science data (see Osborne, Costello, & Kellow, 2008) and retained only items that exceeded this benchmark. After reviewing the content of these items within this new

seven-factor structure, I renamed these factors to better capture each factor's overarching theme. The conceptual evolution of the original six-factor model to the new seven-factor model is shown in Figure 5. The factor loadings are listed in Table 7.

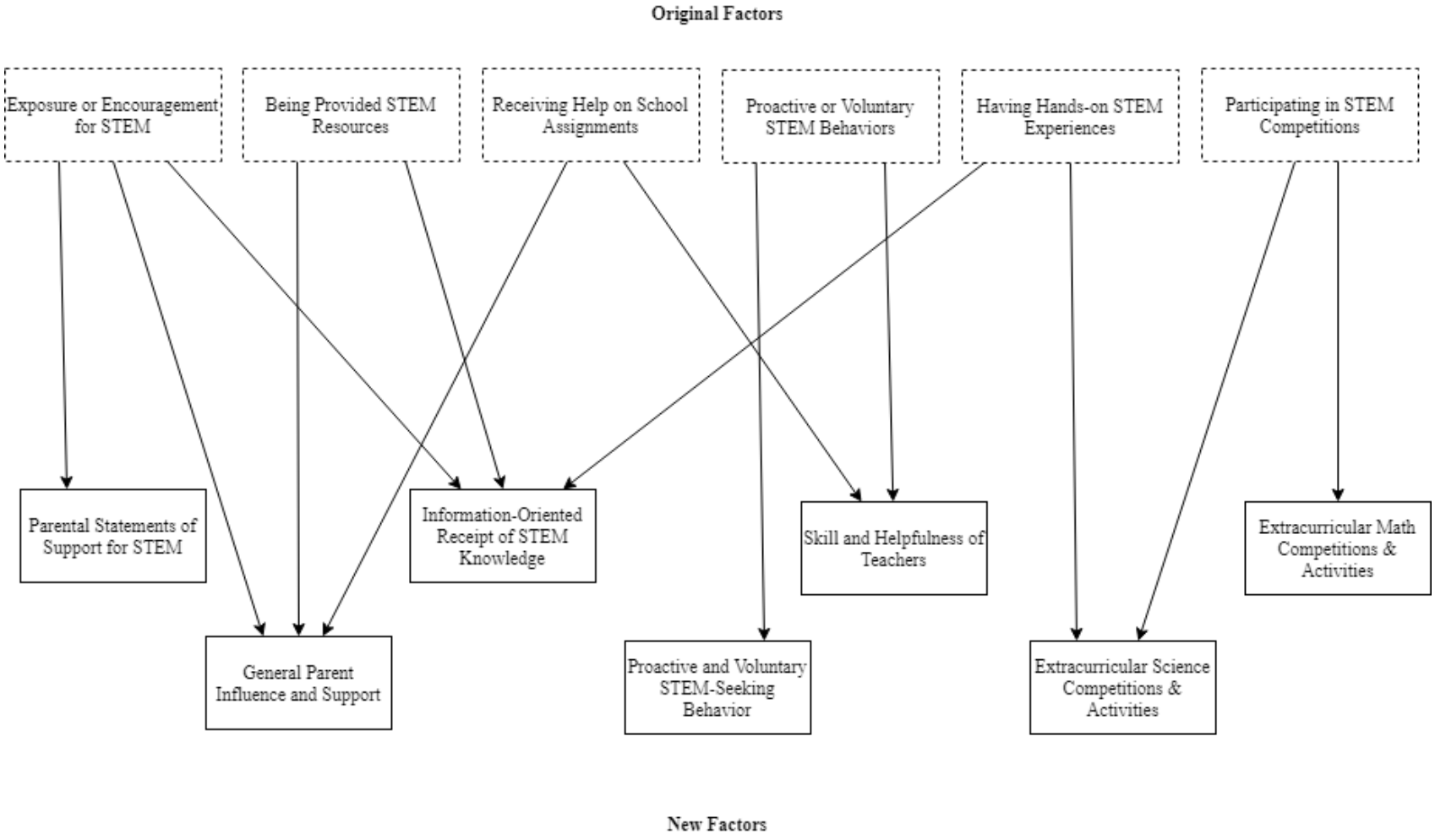

Figure 5. Adapted biodata factor model after Study 1 EFA

Table 7. Factor Loadings of EFA from Study 1

	Item	1	2	3	4	5	6	7
Factor 1: General Parent Influence and Support								
1	How helpful did you think your parents would be if you had trouble with an assignment?	0.860						
2	Ask your parents for help with a class assignment if you were struggling with it?	0.800						
3	How capable were your parents of helping you on a science assignment if you needed help?	0.725						
4	How capable were your parents of helping you on a math assignment if you needed help?	0.714						
5	How often did your parents ask you if you needed help with your homework?	0.667						
6	How often did your parents help you study for tests?	0.642						
7	To what extent did your parents expect you to figure out difficult class assignments on your own? (RC)	0.468						
8	How much influence did your parents have on the school topics you were interested in?	0.451						
9	How willing were your parents to pay for new STEM activities for you to try?	0.450						
10	How willing were your parents or other family members to pay for hands-on STEM project materials for you?	0.426						
11	How much access did you have to hands-on STEM materials at home?	0.408						
12	What proportion of your parents, siblings, or extended family worked in a STEM career while you were growing up?	0.401						

	Item	1	2	3	4	5	6	7
Factor 2: STEM Knowledge and Experiences								
13	How often did adults in STEM careers tell you about their career?		0.599					
14	How often did you work on engineering, building, or construction projects in class?		0.581					
15	How often did adults in STEM careers tell you that you would do well in a similar career?		0.579					
16	How often did you interact with adults in STEM fields who were not related to you?		0.562					
17	How often did your parents or teachers give you STEM-related books, toys, or other STEM gifts?		0.534					
18	How often did you attend one-day science, math, or engineering events, such as talks or demonstrations?		0.515					
19	How often did you go on field trips to activities or places where you were able to touch or build things?		0.479					
20	How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?		0.435					
21	How often did you attend multi-day STEM events, such as STEM-related summer camps?		0.409					
22	To what extent did you look forward to working on hands-on STEM activities in your classes?		0.403					
Factor 3: Extracurricular Math Competitions & Activities;								
23	How often did you participate in math competitions that were voluntary?			0.863				
24	How often did you spend a lot of time after school preparing for math competitions?			0.729				
25	How much did you look forward to opportunities to participate in math competitions?			0.724				

	Item	1	2	3	4	5	6	7
26	How often did you participate in math competitions?			0.649				
27	How often did you work on extracurricular or extra credit math assignments just because you wanted to?			0.424				
Factor 4: Proactive and Voluntary STEM Behavior								
28	How often did you ask for STEM-related gifts for your birthday or another holiday?				0.757			
29	How often did you work on recreational science projects just because you wanted to?				0.742			
30	How often did you ask your parents for parts or materials so you could work on hands-on STEM activities?				0.639			
31	How often did you seek out information on STEM events you wanted to attend?				0.577			
32	How often did you choose to attend or participate in STEM events that were voluntary?				0.433			
33	To what extent did your family provide you with books, movies, or TV shows about a certain STEM career path?				0.406			
Factor 5: Parental Statements of Support for STEM								
34	To what extent did your parents encourage you to work in a specific STEM career because that career would have plenty of jobs available?					0.857		
35	To what extent did your parents encourage you to pursue STEM at the expense of your non-STEM interests?					0.764		
36	Were your parents more likely to pay for you to participate STEM activities than in non-STEM activities?					0.707		
37	How often did your parents talk to you about the importance of choosing a STEM major in college?					0.681		

	Item	1	2	3	4	5	6	7
38	To what extent did your parents encourage you to pursue a STEM interest due to your innate talent or ability for the topic?					0.458		
Factor 6: Skill and Helpfulness of Teachers								
39	How comfortable did you feel asking your teacher science or math questions during class?						0.758	
40	How helpful were most of your teachers if you were struggling with an assignment?						0.738	
41	How skilled were most of your teachers at explaining new topics to the class?						0.685	
42	How willing were you to approach your teacher with science or math questions after class?						0.650	
Factor 7: Extracurricular Science Competitions & Activities								
43	How often did you participate in science competitions?							0.685
44	How often did you work on science fair projects at school?							0.623
45	To what extent did your parents expect you to participate in science competitions?							0.555
46	To what extent did your teachers encourage you to participate in science competitions?							0.548
47	How often did you work on science experiments or projects in class?							0.438

Note. $N = 154$

The first factor (12 items) was “General Parent Influence and Support.” It comprised primarily items from the former “Help from Others” and “Receiving Resources” factors. Sample items include: “How often did your parents ask you if you needed help with your homework?” and “How willing were your parents to pay for new STEM activities for you to try?” The scale’s internal reliability, calculated for all the following measures as Cronbach's (1951) alpha (α) was .909.

The second factor (10 items) was “STEM Knowledge and Experiences.” It comprised primarily items from the former “Exposure to STEM” and “Receiving Resources” categories. Sample items include: “How often did adults in STEM careers tell you that you would do well in a similar career?” and “How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?” (α = .897).

The third factor (5 items) was “Extracurricular Math Competitions & Activities.” It comprised the math items from the original “STEM Competitions factor.” Sample items include: “How much did you look forward to opportunities to participate in math competitions?” and “How often did you spend a lot of time after school preparing for math competitions?” One science-specific item, although it most highly loaded in this category (“How often did you participate in science competitions that were voluntary?”) was relocated into the following (fourth) factor instead for better interpretability. (α = .873).

The fourth factor (6 items) was “Proactive and Voluntary STEM Behavior.” It comprised six of the items from the original “Proactive Behavior” category. Sample items include: “How often did you work on recreational science projects just because you wanted to?” and “Choose to attend or participate in STEM events that were voluntary?” (α = .862).

The fifth factor (5 items) was “Parental Statements of Support for STEM.” It comprised primarily items from the original “Exposure to STEM” factor. Sample items include: “How often did your parents talk to you about the importance of choosing a STEM major in college?” and “To what extent were your parents more likely to pay for you to participate STEM activities than in non-STEM activities?” ($\alpha = .863$).

The sixth factor (4 items) was “Skill and Helpfulness of Teachers.” It comprised primarily the teacher-specific items from the original “Help from Others” factor. Sample items include: “How skilled were most of your teachers at explaining new topics to the class?” and “How helpful were most of your teachers if you were struggling with an assignment?” ($\alpha = .828$).

The seventh factor (5 items) was “Extracurricular Sc ience Competitions & Activities,” which comprised primarily the science-specific items from the “STEM Competitions” factor, as well as the “Hands on STEM Activities” factor. Sample items include “How often did you work on science experiments or projects in class?” and “To what extent did your teachers encourage you to participate in science competitions?” ($\alpha = .839$). The new scale is included in Appendix I, and Cronbach’s alpha for each scale factor are listed in Table 8.

Table 8. Modified Biodata Factors

	Factor	*α*	*n* items	Mean	SD
1	General Parent/Family Influence and Support	.909	12	2.692	0.897
2	Receipt of STEM Knowledge or Experiences	.897	10	2.483	0.855
3	Extracurricular Math Competitions & Activities	.873	5	2.462	0.949
4	Proactive and Voluntary STEM-Seeking Behavior	.862	6	2.554	1.009
5	Parental Statements of Support for STEM	.863	5	2.594	1.065
6	Skill and Helpfulness of Teachers	.828	4	3.328	0.811
7	Extracurricular Science Competitions & Activities	.839	5	2.329	1.063

Note. N = 154

Although I did not have specific hypotheses regarding race and gender effects, based on prior research on inequality and barriers in STEM, race and gender differences seemed to be plausible. I explored group differences using planned contrasts. First, I compared White students to underrepresented minority (Black and Hispanic) students and found two significant relationships among the biodata factors. First, White students reported higher general parental support *(F(*1,144) = 11.473, $p = .001$). Second, underrepresented minority students reported higher parent STEM support *(F(*1,144) = 5.408 $p = .022$). The other biodata factors, including STEM knowledge and experiences *(F(*1,144) = 1.255, $p = .265$), participation in math competitions *(F(*1,144) = 2.799, $p = .097$), proactive behavior (*F*(1,144) = .989 $p = .322$), teacher support *(F(*1,144) = .033 $p = .855$) and science competitions factors were not significant (*F*(1,144) = .217 $p = .642$). See Table 9 for all means by race.

Table 9. Biodata Factor Means by Race

Factor	Race				
	Asian American	Black or African American	Hispanic or Latinx	White or Caucasian	Multi-racial/ Other
General Parent/Family Influence and Support	3.06 (0.95)	2.47 (0.87)	2.45 (0.96)	3.11 (0.68)	2.42 (0.62)
Receipt of STEM Knowledge or Experiences	2.89 (0.90)	2.36 (0.78)	2.35 (0.89)	2.56 (0.78)	2.20 (0.59)
Extracurricular Math Com & Activities	2.46 (0.95)	2.39 (1.11)	2.46 (1.13)	2.04 (0.90)	1.94 (1.15)
Proactive & Voluntary STEM-Seeking Behavior	2.90 (0.96)	2.45 (1.06)	2.50 (0.98)	2.70 (1.09)	2.38 (0.94)
Parental Statements of Support for STEM	3.26 (1.04)	2.67 (1.02)	2.55 (1.09)	2.10 (0.79)	2.09 (0.60)
Skill and Helpfulness of Teachers	3.25 (0.77)	3.33 (0.70)	3.37 (0.87)	3.38 (0.93)	3.25 (0.68)
Extracurricular Science Com & Activities	2.79 (0.96)	2.41 (1.02)	2.40 (0.95)	2.31 (0.89)	2.43 (0.58)

Note. $N = 143$, *SD* in parentheses

Next, I compared biodata factor means by gender. There were no significant differences between any of the biodata factors, although the parental statements of support for STEM factor was marginally significant ($p = .093$), in favor of slightly greater support reported by female participants. See Table 10 for all biodata factor means by gender.

Table 10. Biodata Factor Means by Gender

Factor	Gender		Test of Mean Differences	
	Female	Male	*t*	*p*
General Parent/Family Influence and Support	2.76 (0.90)	2.54 (0.87)	1.498	.346
Receipt of STEM Knowledge or Experiences	2.51 (0.80)	2.42 (0.95)	0.633	.528
Extracurricular Math Comp & Activities	2.39 (1.11)	2.22 (0.99)	0.939	.349
Proactive & Voluntary STEM-Seeking Behavior	2.63 (1.03)	2.42 (0.96)	1.227	.222
Parental Statements of Support for STEM	2.70 (1.12)	2.40 (0.90)	1.692	.093
Skill and Helpfulness of Teachers	3.34 (0.77)	3.30 (0.89)	0.318	.751
Extracurricular Science Comp & Activities	2.52 (0.95)	2.35 (0.95)	1.031	.304

Note. $N = 154$, *SD* in parentheses

In aggregate, the seven factors showed significant small to medium intercorrelations. Effect sizes were defined based on the guidelines provided by Cohen (1988), with .10, .30, and .50 representing approximately small, medium, and large correlation effect sizes, respectively. See Table 11 for all factor intercorrelations. The largest correlation was between participating in science competitions and other activities and receiving STEM-related knowledge or experiences (r = .657). Because this correlation was relatively large in magnitude, I compared a CFA using a model with the seven factors and one with six factors in which the science competitions and STEM-related knowledge and experiences were combined. Results showed that the seven-factor model was still a better fit. The smallest correlation was between explicit parental messages of support for STEM and skill and helpfulness of teachers (r = .225). I also re-wrote the twelve items I eliminated due to poor fit in the EFA to target them intentionally for one of the seven factors. The modified measure, including identification of the rewritten items, is included in Appendix I.

Table 11. Intercorrelations of Biodata Factors

	Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	General Parent/Family Influence and Support	(*.909)*						
2	Receipt of STEM Knowledge or Experiences	.546**	*(.897)*					
3	Extracurricular Math Competitions & Activities	.248**	.457**	*(.873)*				
4	Proactive and Voluntary STEM-Seeking Behavior	.422**	.593**	.509**	*(.862)*			
5	Parental Statements of Support for STEM	.449**	.471**	.313**	.370**	*(.863)*		
6	Skill and Helpfulness of Teachers	.345**	.357**	.336**	.274**	.225**	*(.828)*	
7	Extracurricular Science Competitions & Activities	.450**	.657**	.507**	.551**	.416**	.413**	*(.839)*

Note. Reliability estimates are calculated as Cronbach's alpha (Cronbach, 1951) in parentheses on the diagonal; *N = 154*

Construct Validity

I examined the other constructs assessed in the study for convergent and discriminant validity, including students' elementary school experiences, psychological and STEM-specific traits, and high school science and math preparation. Reliability estimates and descriptive statistics are shown in Table 12. On average, students had attended 1.89 elementary schools from kindergarten through fifth grade (*SD* = 1.09), had a 726.49 average SAT Math score (*SD* = 48.95), a 31.14 ACT Math score (*SD* = 2.48), and had taken 3.34 STEM AP classes (*SD* = 1.62) in high school. For context, a 726 SAT Math score is within the 94th to 95th percentile of all test takers; a 31 ACT Math score is approximately the 96th percentile.

Table 12. Academic, Social, and Personality Scale Reliabilities in Study 1

Measure	***α***	***n* items**	**Mean**	**SD**
Elementary School Education				
Educational Quality	.866	8	3.89	0.710
Availability of Books	-	1	3.09	1.295
Number of Schools Attended	-	1	1.89	1.090
Psychological Characteristics				
Proactivity	.905	10	3.13	0.843
STEM Self-Efficacy	.937	9	4.44	1.171
STEM Career Expectations	.930	4	4.22	1.036
STEM Identity[a]	.879	10	3.56	0.824
Personality				
Openness to Experience	.756	4	3.85	0.850
Agreeableness	.800	4	3.93	0.857
Entry Academic Characteristics				
Math SAT Score	-	1	726.49	48.946
Math ACT Score	-	1	31.14	2.447
Entering STEM Credits	-	1	3.34	1.624

Note: N = 150, [a]This measure was administered during a previous time period (Fall 2019)

All seven biodata factors showed non-significant or significant but small effects with openness to experience and agreeableness. As expected, students who had more STEM-related

experiences and more opportunities to learn about STEM tended to have greater openness to experience (r = .225), supporting Hypothesis 1. However, this was a slightly smaller correlation than the anticipated medium-sized (r = .300) effect. Hypothesis 2 was not supported, as multiple small but significant correlations were found between agreeableness and biodata factors. Students who participated in math competitions were slightly more likely to be agreeable (r = .195), and students who exhibited voluntary and proactive STEM behavior were slightly more open to experience. Students who perceived favorable experiences with their teachers were more likely to be agreeable (r = .202), as were students who participated in science competitions and activities (r = .162). Parental support of students pursuing STEM did not correlate significantly with any personality trait. See Table 13 for all correlations between biodata factors and personality traits.

Table 13. Correlations between Biodata Factors and Personality Traits

	Biodata Factor	**Openness to Experience**	**Agreeableness**
1	General Parent/Family Influence and Support	.107	.074
2	Receipt of STEM Knowledge or Experiences	.225**	.117
3	Extracurricular Math Competitions & Activities	.079	.195*
4	Proactive and Voluntary STEM-Seeking Behavior	.181*	.164*
5	Parental Statements of Support for STEM	.035	.155
6	Skill and Helpfulness of Teachers	.144	.202*
7	Extracurricular Science Competitions & Activities	.044	.162*

*Note: N = 150; * p < .05, ** p < .01*

Of the STEM-specific constructs, STEM identity had small but significant correlations with three of the biodata factors, including math competitions and activities (r = .272), proactive and voluntary behavior (r = .250) and teacher support (r = .279). STEM self-efficacy had

relatively small correlations with four of the biodata factors, including general parental support (r = .278), STEM knowledge and experiences (r = .197), proactive and voluntary behavior (r = .210), and extracurricular science activities (r = .167). STEM career expectations had small correlations with proactive and voluntary behavior (r = .170) and teacher support (r = .167). Proactivity had significant small correlations with five of the biodata factors, including STEM knowledge and experiences (r = .225), extracurricular math activities (r = .243), proactive and voluntary behavior (r = .294), parental support of STEM (r = .180), and teacher support (r = .188), which supported Hypothesis 3. See Table 14 for all correlations.

Table 14. Correlations between Biodata Factors and STEM Variables

	Biodata Factor	**STEM Identity**	**STEM Self-Efficacy**	**STEM Career Expectations**	**Proactivity**
1	General Parent/Family Influence and Support	-.004	.278**	.150	.121
2	Receipt of STEM Knowledge or Experiences	.105	.197*	.099	.225**
3	Extracurricular Math Competitions & Activities	.272*	.106	.089	.243**
4	Proactive and Voluntary STEM-Seeking Behavior	.250*	.210*	.170*	.294**
5	Parental Statements of Support for STEM	.060	.106	.037	.180*
6	Skill and Helpfulness of Teachers	.279*	.097	.167*	.188*
7	Extracurricular Science Competitions & Activities	.136	.167*	.044	.133

*Note: N = 150; * < .05, ** < .01*

Among elementary school experiences, many factors had small to medium correlations with the educational opportunities scale and in the availability of books in students' households growing up, generally supporting Hypothesis 4 (with the context of the biodata structure being slightly different from the factors referenced in the original hypothesis). One of the largest

correlations was between participating in extracurricular science activities and having greater educational opportunities (r = .504). Further, the general parental influence factor showed a medium positive correlation (r = .552) with students' availability of books. The number of elementary schools that students attended had a small positive correlation (r = .166) with the perceived helpfulness of teachers. The number of schools attended did not have significant correlations with any other biodata factor, providing partial support for Hypothesis 5. See Table 15 for all correlations between biodata factors and elementary school variables.

Table 15. Correlations between Biodata Factors and Elementary School Education

	Biodata Factor	**Education Opportunities**	**Availability of Books**	**Number of Schools**
1	General Parent/Family Influence and Support	.331**	.552**	.027
2	Receipt of STEM Knowledge or Experiences	.296**	.399**	.046
3	Extracurricular Math Competitions & Activities	.124	-.033	.064
4	Proactive and Voluntary STEM-Seeking Behavior	.124	.303**	.011
5	Parental Statements of Support for STEM	.047	.202*	.024
6	Skill and Helpfulness of Teachers	.504**	.108	.166*
7	Extracurricular Science Competitions & Activities	.378**	.292**	.120

*Note: N = 150; * < .05, ** < .01 *** < .001*

Next, I examined the correlations between biodata factors and STEM high school preparation. Most factors had non-significant to small correlations with math standardized test scores. STEM knowledge and experiences (r = .247) and proactive and voluntary behavior (r = .288) had the largest correlations. None of the factors correlated significantly with high school STEM preparation. See Table 16 for all correlations between biodata factors and STEM high school preparation.

Table 16. Correlations of Biodata Factors with STEM High School Preparation

	Biodata Factor	Math ACT/SAT	STEM AP Credits
1	General Parent/Family Influence and Support	.193*	-.129
2	Receipt of STEM Knowledge or Experiences	.247**	-.028
3	Extracurricular Math Competitions & Activities	.137	.002
4	Proactive and Voluntary STEM-Seeking Behavior	.228*	.113
5	Parental Statements of Support for STEM	.115	.054
6	Skill and Helpfulness of Teachers	.105	.022
7	Extracurricular Science Competitions & Activities	.048	.112

*Note: N = 150; * < .05, ** < .01*

Discussion

After conducting a CFA as originally proposed on the biodata measure, I found insufficient fit to proceed with analysis and interpretation of the model. As a result, I ran an exploratory factor analysis, which found support for a seven-factor solution. After examining factor loadings and item content, I re-categorized the items and re-named the factors to capture the content the factors contained. I also re-wrote 12 items (out of the original 60 items) that did not load cleanly onto any factor to target them toward a specific factor for confirmatory factor analysis in Study 2.

The first factor, "General Parent Influence and Support," represented a general (i.e. not STEM-specific) parental influence factor. It comprised primarily items from the former "Help from Others" and "Receiving Resources" factors. I originally conceptualized the factors as being divided between receiving help through interpersonal support and receiving physical or financial resources. However, based on the factor loadings, the clearer distinction appeared to be between receiving general support and resources and receiving STEM-specific support and resources.

The second factor, “STEM Knowledge and Experiences,” represented non-competitive experiences in which students learned about STEM topics. It comprised primarily items from the former “Exposure to STEM” and “Receiving Resources” categories. Again, students did not appear to perceive a distinction between receiving resources and receiving verbal support. Instead, the distinction appeared to be whether the support was STEM-specific.

The third factor, “Extracurricular Math Competitions & Activities,” comprised the math items from the original “STEM Competitions” factor. It represented a need to reframe my original conceptualization that participation in math and science competitions captured the same construct. Students appear to experience math competitions differently from science competitions, and there may be little to no correlation between having science and math competitions or experiences. The factor structure also implied that students who participate in math competitions may also enjoy other extracurricular math activities.

The fourth factor, “Proactive and Voluntary STEM Behavior,” comprised six of the items from the original “Proactive Behavior” category. This finding meant that the original factor structure that included proactive behavior as a distinct construct was supported, albeit with the need to remove some items that were better categorized under different factors.

The fifth factor, “Parental Statements of Support for STEM,” comprised primarily items from the original “Exposure to STEM” factor. It consisted of items representing parents verbalizing support for their children pursuing a STEM interest or career, or providing the resources to do so. As previously discussed, I had not anticipated that students would be able to differentiate clearly between their parents supporting them academically in general and with STEM in particular, but this emerged as a clear distinction in these data.

The sixth factor, “Skill and Helpfulness of Teachers,” comprised primarily the teacher-specific items from the original “Help from Others” factor. It consisted of the influence of teachers in providing support, or being perceived as willing to do so, to students. Students appeared to experience support and help from their teachers differently from these same experiences with their parents, and the two experiences were not interchangeable or necessarily similar.

The seventh factor, “Extracurricular Science Competitions & Activities,” comprised primarily the science-specific items from the “STEM Competitions” factor, as well as the “Hands on STEM Activities” factor. As discussed with the math competitions factor, students did not necessarily like or participate in both math and science competitions. The students who enjoyed and participated in science competitions also tended to enjoy extracurricular science activities and hands-on activities.

Examining differences by race and gender, White students reported higher general parental support but lower parental STEM support than underrepresented minority (Black and Hispanic) students. White parents may have benefited from a position of relative privilege in society and greater knowledge of how to advocate for their children in American elementary schools. The parents of underrepresented minority students, conversely, appeared to place a greater value on the utility of obtaining a STEM degree and pursuing STEM interests than White parents did, perhaps as a result of prioritizing their children obtaining a relatively secure and/or high-paying job in an uncertain professional world that might disadvantage employees from underrepresented backgrounds. The other biodata factors, including STEM knowledge and experiences, participation in math competitions and extracurricular activities, proactive STEM

behavior, teacher support, and participation in science competitions and extracurricular activities, were not significantly different by race.

Regarding gender, there were no significant differences between any of the biodata factors, although the parental STEM support factor was marginally significant in favor of slightly greater support reported by female participants. Based on prior research on gender differences in elementary school STEM experiences, this finding might appear to be counterintuitive; however, parents may have perceived that their daughters would benefit more from explicit support to pursue STEM due to awareness of gender barriers in STEM fields. An alternate explanation might be that female students who persisted to the point of matriculating as a STEM major at Rice may have required stronger parental support to persist in STEM.

Many of the correlations between the biodata factors and math standardized tests scores were small, with significant but small positive correlations suggesting that students who perceived higher general academic support from their parents, had learned about STEM, and who had voluntarily sought out STEM activities and knowledge in elementary were more likely to have higher math standardized test scores in high school. Conversely, participating in science or math competitions, receiving STEM-specific encouragement from parents, and having helpful, skilled teachers in elementary school did not contribute to math standardized test scores. These results suggest that elementary school students who tend to build STEM-specific knowledge, especially if done so proactively, with the support of their family are those who will perform most highly on the math ACT and SAT sections.

Students' STEM identity demonstrated small correlations with their participation in math competitions, their tendency to voluntarily seek STEM knowledge, and the skill and support of their teachers. These small correlations may be a function of range restriction in this sample,

which comprised students who were generally highly interested in STEM topics and had high STEM identities. Neither general parental support nor support for STEM appeared to correlate with students' STEM identity. These findings may indicate that parents are more able to impact their children's behavior than their identity. However, parents may also be able to impact their children's self-efficacy in STEM subjects. STEM knowledge and experiences, proactive and voluntary behavior, and science competitions and activities all demonstrated small correlations with self-efficacy, as well. With general parental support in their lives, students appear to also become efficacious in STEM topics as a result of gaining STEM knowledge, proactively seeking STEM experiences, and participating in science competitions and extracurricular activities. Only proactive and voluntary behavior, as well as teacher skill and helpfulness, contributed to students' intentions of having a STEM career. By the time students reach college age, their career expectations may have diverged markedly from the influence that elementary school experiences provided them. Finally, proactivity had small correlations with five biodata factors. Students who had more STEM knowledge and experiences, participation in math competitions, STEM-specific parental support, helpful teachers, and, unsurprisingly, more proactive and voluntary behavior, all demonstrated higher proactivity. Perhaps students who are more interested in STEM topics (or who have any targeted interest) tend to be more proactive. This potential explanation may be supported by the fact that parental support for STEM predicted proactivity, but general academic support did not. Finding and having STEM experiences, as well as participating in math competitions, may also intrinsically require higher levels of proactivity. Regardless of causality, proactivity appears to play a significant, albeit minor, role in STEM formative experiences.

Several of the correlations between biodata factors and elementary school characteristics are worth noting. For example, the medium-sized correlation between participating in extracurricular science activities and having greater educational opportunities may support the previously-discussed research describing how lower-resourced elementary schools offer less access to science supplies and equipment than other elementary schools. The correlation between parental involvement and book availability might be explained by parents who are actively involved in supporting their children's academic success being more likely to provide their children with greater access to books at home. The small positive correlation between the number of elementary schools that students attended and the perceived helpfulness of their teachers was somewhat surprising, in the context of research on the negative impact of frequently changing schools on many student outcomes. One explanation could be that students who frequently changed schools necessarily had greater interaction with their teachers than children who remained at their original elementary school, but this finding would need to be replicated in a future study before stronger conclusions should be made.

There were also generally small correlations between openness to experience and agreeableness with the biodata factors. Interestingly, although the expected link between openness to experience was found with the biodata measure, it was only significant in two factors (STEM knowledge and experiences and proactive and voluntary STEM behavior), and both were small correlations. Agreeableness correlated most of the biodata factors, including participation in math competitions, proactive behavior, teacher skill and helpfulness, and science competitions. Each of these factors represent outward-facing behavior or interactions, and agreeable children may be more likely to seek out certain experiences or interactions, or to have parents or teachers expose them to these experiences. The relationships between the components

of STEM formative experiences and personality traits may be more nuanced than previously recognized, with different personality traits contributing to different experiences (and perhaps perceptions of outside experiences) by students.

This study allowed for a more refined measure of STEM formative experiences to be developed after the first step in validating the measure on a sample of STEM students (see Appendix I). After reframing and reallocating items to a modified factor structure, many of the factors demonstrated the expected correlations with other constructs and were interpretable; however, these correlations were in many cases relatively small. Given the large time gap between the end of elementary school and students' time in college, many other factors could also impact students' STEM performance, behavior, and other variables. However, the fact that significant correlations were found at all is promising and supports the value of further refining the measure and testing its predictive validity on long-term outcomes. Further, it is worth noting that the students in this study were not only academically successful in high school, they also declared a STEM major upon matriculation to Rice (although many students later left STEM). Range restriction in this sample of highly STEM interested students may have reduced the strength of correlations found, compared to administering this measure on a broader sample of students. However, a strength of this sample was in ensuring that many of these students would presumably have significant early experiences in science or math that a biodata measure could capture. Regardless, the broader validity of the biodata measure will need to be established on a wider (i.e. not STEM-specific) sample.

CHAPTER 5: STUDY 2

Study 1 produced a more refined version of the biodata measure with a different factor structure than originally hypothesized (see Appendix I), which was then used for validation on a sample of students from varied majors and backgrounds in Study 2.

Participants

Participants were 175 college freshmen enrolled in psychology classes at Rice who registered for the study through the experimental pool of students (SONA). This sample size approaches recommended samples of 200 for SEM (Weston & Gore, 2006). A post-hoc power analysis of the final version of this model showed that this analysis was sufficiently powered ($\beta = .99$) to find significant effects, based on an RMSEA of 0.05 and an alpha of .05 (MacCallum et al., 1996). Participants were 39.4% Asian ($n = 67$), 35.3% White ($n = 60$), 10.6% Hispanic or Latino ($n = 18$), 8.8% Black or African American ($n = 15$) and 5.9% multiracial or other ($n = 10$). They were 62% female ($n = 105$).

Measures

Biodata questionnaire. The updated, 60-item, seven-factor version of the survey after completing Study 1 was administered. See Appendix I for all items. On each section, students were shown the prompt: “When you were elementary school age (11 and younger)...” Items included “What proportion of your parents, siblings, or extended family worked in a STEM career while you were growing up?” and “How often did you interact with adults in STEM fields who were not related to you?” All items were scored on a five-point Likert scale, with labels appropriate to the question, including *1 = Never* to *5 = Always or Almost Always* and *1 = Not at All* to *5 = Completely or Fully.*

SCCT items. It is generally recommended to use at least two measures to capture each construct in a structural equation model (Weston & Gore, 2006); therefore, career outcome expectancies, self-efficacy, and interest were measured with two or three established scales, with items altered when necessary to be appropriate for college students. These measures were chosen to correspond with the constructs in the SCCT model (see Figure 3 on page 48 for the originally tested model). Internal consistency of the scales are provided using Cronbach's alpha (Cronbach, 1951) when available.

STEM interest. The first interest scale was a six-item math interest inventory (Frenzel, Goetz, Pekrun, & Watt, 2010) that assesses personal interest via both cognitive and affective components on a five-point Likert scale ranging from *1 = Strongly Disagree* to *5 = Strongly Agree*. I adapted items slightly to refer to college-level math work. Items include: "I like to read non-fiction books related to mathematics" and "After a math class, I am often curious about what we are going to do in the next lesson." Cronbach's alpha was .78 when the original scale was administered to ninth grade students.

The second STEM interest scale was an eight-item STEM career interest inventory (Milner et al., 2014), which asks respondents how interested they would be in performing various STEM-related activities. Responses are scored using a 5-point Likert scale ranging from *1 = Strongly Disinterested* to *5 = Strongly Interested*. Items include: "Redesign an engine to improve fuel efficiency" and "Measure the speed of electrons." Cronbach's alpha was .91 on the short version of the original scale.

STEM self-efficacy. For math self-efficacy, I adapted two items from a middle school self-efficacy questionnaire (Fouad et al., 1997), to be appropriate for college students, as well as six items from Betz and Hackett's (1983) college math self-efficacy scale. Participants are

instructed to indicate their ability to do each item on a Likert scale from *1 = Very High Ability* to *5 = Very Low Ability.* Items include: “Get an A- or higher in upper-level math classes.” and “Compute your car’s gas mileage.”

For science self-efficacy, I adapted ten items from a questionnaire by Smist (1993) to be appropriate for college students. Participants are instructed to indicate their ability to do each item on a Likert scale from *1 = Very High Ability* to *5 = Very Low Ability.* Items include: “Understand abstract chemical concepts” and “Understand concepts in a college biology textbook.”

For college major self-efficacy, I used the educational requirements subscale from Betz and Hackett (1981). I listed STEM majors (e.g. engineering, physics) as options, plus the most common non-STEM majors (e.g. English, psychology) based on the National Center for Education Statistics' (2018) list of most popular majors. Participants were instructed to indicate their level of confidence in being able to complete the requirements for each major on a Likert scale from *1 = Completely Unsure* to *10 = Completely Sure*. I used only STEM majors (all majors in the School of Natural Sciences and the School of Engineering) in the analysis.

Career outcome expectations. I used two established scales for career outcome expectations in math and science careers. The first is the 12-item Mathematics & Science Career Outcome Expectancies scale (Fouad et al., 1997). This was originally a middle school scale that I altered slightly for college students (primarily by changing items to refer to students’ college and post-college plans rather than high school plans). Items include: “If I learn math well, then I will be able to do lots of different types of careers” and “I am determined to use my science knowledge in my future career.” The scale is scored on a Likert scale ranging from *1 = Strongly Disagree* to *5 = Strongly Agree.*

The second scale was the Career Outcome Expectations scale (Hazari et al., 2010), which was originally developed to assess the physics identity of high school students. I adapted the items slightly to refer to graduating from college. Students respond using a six-point Likert scale ranging from *1 = Not at all important* to *6 = Very important.* Respondents are instructed to rate these items in terms of their importance for their future career satisfaction. Items include: "Inventing new things" and "Working with people rather than objects." The four items related to intrinsic fulfillment, the only factor found to predict physics identity in this study, were used.

Choice goal and choice action. The choice goal in this study was students' originally intended college major upon matriculation. The choice action was students' intended major after their second semester. Each major was rated on Goldman and Hewitt's (1976) science-nonscience continuum, which ranges from 5 (natural sciences and engineering; e.g., physics), 4 (biological and health sciences), 3 (business and social sciences), 2 (humanities) or 1 (fine arts). This assessment procedure has been used in prior studies (e.g. (Pajares & Miller, 1995) to operationalize how different college majors fit into a framework of STEM orientation.

Finally, to provide another measure to capture students' choice goals and choice actions, career plans were assessed as 1) students' original career plans when they entered Rice and 2) their current career plans. Similar to students' intended and actual majors, industries were based on their rankings on science-nonscience continuum. Specifically, selections for "Engineering," "Information Technology and Computer Science" and "Science or Math" were rated as a 5. "Health and Medical Sciences" were ranked as a 4. All other industries were coded on the same science-nonscience continuum described above. The list of industries comes from the U.S. Department of Labor's Occupational Information Network (O*NET) national list of industries (National Center for O*NET Development, 2020). I modified the list to delineate between

science and math versus engineering, added computer science to the information technology item, and edited the health sciences option to explicitly describe practitioners. See Appendix J for the modified list of industries.

Other measures. In order to control for potential confounds in the analyses, the following measures were also used.

Proactivity. The same ten-item measure of proactive behavior by Seibert et al. (1999) used in Study 1 was used in this study.

Perceptions of course grades and course effort. Students were asked to assess their perceptions of the effort they exerted their previous semester and the current semester, on a Likert scale from *1 = Minimal Effort* to *5 = The Maximum Amount of Effort*. Satisfaction with grades for both the previous and current semesters were assessed on a Likert scale from *1 = Very Unsatisfied* to *5 = Very Satisfied*.

High school coursework and standardized test scores. Students self-reported the AP STEM classes they successfully completed in high school, as well as their SAT and/or ACT scores for each section (math, science, reading, and writing for the ACT; math and reading for the SAT). I used only math SAT and math ACT scores for this study. I converted ACT math scores to SAT math scores when students only reported results from the ACT using the conversion guide provided by the ACT (ACT, 2018). I expected students' math scores to correlate with their STEM career outcome expectancies.

AP tests and Rice course records. The university registrar's office provided participants' 1) STEM AP credits transferred to the university and 2) first semester course grades (from which I calculated their first semester STEM GPA). I expected students' AP credits to correlate with

their initial STEM major, and students' STEM GPAs to correlate with their intended major. See Figure 6 for the model to be tested in the structural equation model.

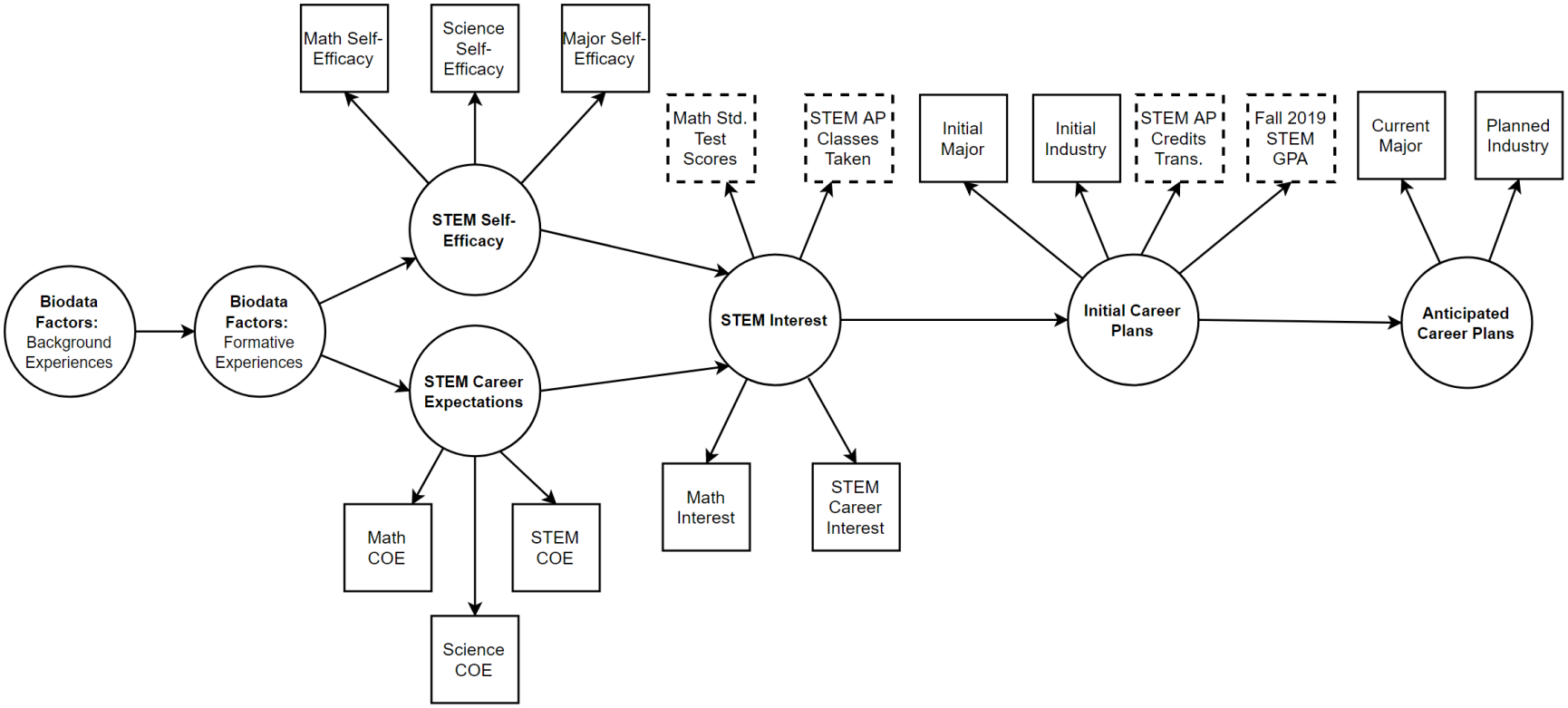

Figure 6. Adapted SCCT model for Study 2; solid boxes represent subjective data collected from participants; dashed boxes represent objective data obtained from the either the registrar's office or self-reported by students.

Procedure

I administered the biodata questionnaire to students using Qualtrics, which incorporated a web portal provided by the registrar's office that allowed students to consent to providing their course records. Similar to the survey design considerations of Study 1 in terms of minimizing common method bias, I included each scale on separate pages, assured participants that their responses would be kept anonymous, and instructed participants that there were no wrong answers. Students received one hour of research credit for completing the survey. To further reduce common method bias, I used academic records from the university registrar's office. After all survey data were collected, the university registrar's office provided participants' academic records. I linked the academic records to students' survey responses, anonymized the data, and then imported the data into R for confirmatory factor analysis using the latent variable analysis (*lavaan*) package. I then used structural equation modeling to test the full model with the biodata measure included.

Results

Of the original 175 responses, one was removed as an outlier for the survey duration being too low. I set a minimum of 300 seconds, or five minutes, to be able to thoughtfully complete the survey. Then, four outliers were removed using the Mahalanobis distance technique, a multivariate approach designed to identify participants whose responses do not have the anticipated correlations with each compared to other participants (Leys et al., 2018). I ran outlier analyses twice, using a standard approach of a chi-square of $p < .001$ as the threshold for outlier identification. The first analyses used the correlation among all items on the educational quality scale because, which had a reverse coded item and might be more likely to capture careless responses. The four participants removed from the data set had negative covariance on

this scale. I also ran this analysis on the multivariate relationships among the two STEM interest and three STEM career interest scales and found no further outliers. Therefore, the following analyses were conducted on the remaining (N = 170) participants. Demographic data are reported in Table 17.

Table 17. Study 2 Participant Demographics

	Gender			
Race	Female	Male	Total *n*	Total as Percentage
Asian	43	24	67	39.4%
Black or African American	11	4	15	8.8%
Hispanic or Latino	9	9	18	10.6%
Multiracial or Other	5	5	10	5.9%
White or Caucasian	37	23	60	35.3%
Total	**105**	**65**	**170**	**100%**

Confirmatory Factor Analysis

First, I conducted reliability analyses on the individual factors of the biodata measure. Three items were removed from the subsequent analyses due to low or negative correlations with other scale items. Addressing Research Question 3, a confirmatory factor analysis was then conducted on the 57-item scale, with the seven latent factors previously discussed. The Comparative Fit Index (*CFI*) of the model was .757 ($\chi^2(924) = 2136.14$, *TLI* = .739, *RMSEA* = 0.087), which is low (a benchmark for the minimum acceptable level of fit is 0.90; Hu & Bentler, 1999). Two factors in particular – STEM Knowledge/Education and Voluntary STEM Behavior – had multiple significant correlations with other factors. Unsurprisingly, removing both factors and their corresponding items improved the fit of the CFA (*CFI* = .933). However, because these

items were created based on earlier qualitative item development and theoretical rationale, I elected to retain them in the model.

Because the fit was worse than the generally accepted minimum of .90 for an acceptable fit to a CFA model (Bentler, 1990), I examined the modification indices for items that did not load highly onto the *a priori* proposed factors. Modification indices are estimates of the change in the chi-square from the current model in terms of improving a model fit if certain restrictions on the model (such as factor loadings or correlation residuals) are changed (MacCallum & Austin, 2000). Because I was interested in identifying poorly loading items while retaining the originally proposed structure of the model, I only examined items with poor factor loadings in the modification indices. I determined that 15 of the items had high modification indices that indicated unanticipated loading onto latent factors other than the ones I proposed.

I compared these items to the modification indices of items from Study 1 to determine if there was overlap among items that did not load cleanly onto individual factors in both studies. Finding that there was overlap with items in the previous study would provide further evidence that the item itself was problematic, rather than specific to Study 2's sample. Six of the 15 items identified in this study were similar or identical to items with high modification indices in Study 1, providing some support for the appropriateness of removing these items from the analyses.

The remaining items that were unique to this study in terms of high cross loadings appeared to be primarily a result of the reclassification of factors after the proposed structure evolved from the original six-factor model to the seven-factor solution. Notably, several items hypothesized to represent parental support for STEM and items designed to represent general parental support had high cross-loadings onto the other factor. Because the results of the factor analysis for both studies showed support for these being two distinct constructs, I rewrote these

items to attempt to better differentiate between the two constructs in future studies. For most of the remaining items, there was general overlap among STEM knowledge, parental support of STEM, and voluntary STEM behaviors. Again, because the CFA showed support for a seven-factor solution and thus these three factors being conceptually distinct, I re-wrote these items as well. All identified items (including items similar or identical to those identified in Study 1) and proposed changes to the items to more explicitly load onto the hypothesized scales are listed in Table 18.

Table 18. Items Removed after CFA in Study 2

No.	Original Item	Unanticipated Loadings	Hypothesized Explanation	New Item
1	How capable were your parents of helping you on a math assignment if you needed help?	Teachers (negative correlation)	Students perceived both their parents and teachers as resources and relied on parents if teachers were insufficient	How capable were your parents of helping you with math assignments?
2	How capable were your parents of helping you on a science assignment if you needed help?	Parents STEM	Parents' help can be perceived as both generally supportive and as STEM-specific	How capable were your parents of helping you with science projects if you needed help?
3	How willing were your parents or other family members to pay for hands-on science, math, or engineering project materials for you?*	Parents Help	Parents' help can be perceived as both generally supportive and as STEM-specific	How interested were your parents or other family members in finding hands-on science, math, or engineering project materials they thought you would you like?
4	How willing were your parents to pay for new science, math, or engineering activities for you to try?*	Voluntary Behaviors	Parents' willingness was likely impacted by students' proactivity and voluntary behavior.	To what extent did your parents prefer to pay for new science, math, or engineering activities for you to try, compared to other activities?
5	How much access did you have to hands-on science, math, or engineering materials at home?*	Voluntary Behaviors, STEM Knowledge, Science and Math Competitions	Overlap in interest, behavior, and availability of resources	How much did you prefer to work with hands-on science, math, or engineering materials at home?
6	How much did you look forward to participating in science competitions?	Voluntary Behaviors, STEM Knowledge	Students who looked forward to science fair competitions were also likely voluntarily pursuing them	How much did you look forward to participating in mandatory science fairs?
7	How often did you attend multi-day science, math, or engineering events, such as summer camps?	Parents STEM, Voluntary Behaviors	Parents likely supported these events so were willing to pay for them; students also likely were willing to attend them. Change item into Parents STEM factor.	How likely were your parents to enroll you in multi-day science, math, or engineering events, such as summer camps?
8	How often did you attend one-day science, math, or engineering events, such as talks or demonstrations?	Math Competitions	Respondents perceived math competitions similarly to STEM events.	How often did you attend non-competitive science, math, or engineering events, such as talks or demonstrations?

No.	Original Item	Unanticipated Loadings	Hypothesized Explanation	New Item
9	How often did you choose to attend or participate in science, math, or engineering events that were voluntary?*	Math Competitions	Respondents perceived math competitions as voluntary	How often did you choose to attend non-competitive science, math, or engineering events?
10	How often did you go on field trips to activities or places where you were able to touch or build things?	Teachers	Students who attended schools with better teachers likely experienced higher quality field trips	How much did you enjoy field trips to places where you were able to touch or build things?
11	How often did you talk to relatives (e.g. older cousins or siblings) who were studying science, math, or engineering in college about their major?*	Parents STEM	Respondents could perceive parents as relatives, despite not being in the description.	How often did you talk to older siblings, cousins, or friends who were studying science, math, or engineering in college about their major?
13	How often did adults in science, math, or engineering careers tell you about their career?	Voluntary Behaviors	Presumably because adults communicated with the student in response to the student's interest.	How often did adults in science, math, or engineering careers want to talk to you about their career?
14	To what extent did your parents encourage you to pursue a science, math, or engineering interest due to your innate talent or ability for the topic?	STEM Knowledge, Voluntary Behaviors	Altered to focus on parents' perceptions of the innate talent of their child, because parents could be responding to students' voluntary behavior	To what extent did your parents believe you had innate talent in a science, math, or engineering topic?
15	To what extent did your parents expect you to participate in non-required science competitions?*	Parents STEM, STEM Knowledge	Altered to remove the reference to parents.	To what extent did you want to participate in non-required science competitions?

Note. * Similar or identical item had high modification index in Study 1

Using the modified version of the scale, I ran a confirmatory factor analysis to determine how well the data fit the new scale. The modified model showed acceptable fit (*CFI* = .919) for the data. See Table 19 for all models run. All following analyses were conducted on the refined 45-item measure.

Table 19. Test of Model on Refined Measure

NF	**Model Description**	**Chi-square**	***df***	***CFI***	***TFI***	***SRMR***
Full models						
7	Originally Proposed Model	5972.17	990	.757	.739	.010
7	Modified Model	502.89	278	.919	.912	.066
Reduced models (after improving fit)						
6	Six-factor model without Math Competitions factor	362.10	194	.901	.882	.069
6	Six-factor model without Parents Help factor	383.06	194	.913	.896	.067
6	Six-factor model without Parents STEM factor	411.11	215	.907	.891	.065
6	Six-factor model without Science Competitions	396.86	215	.914	.899	.066
6	Six-factor model without STEM Knowledge factor	327.40	194	.938	.927	.063
6	Six-factor model without Teachers factor	336.50	194	.926	.914	.064
6	Six-factor model without Voluntary Behavior factor	370.11	194	.912	.896	.066
5	Five-factor model without STEM Knowledge and Voluntary Behavior	244.37	125	.933	.918	.064
Aggregated models						
4	Four-factor model aggregating Science Competitions, STEM Knowledge, and Voluntary Behavior into a single factor	610.15	289	.871	.854	.072
1	All items were loaded onto a single factor	1668.53	299	.448	.400	.139

Note. N = 170. NF = number of factors in model; df = degrees of freedom; CFI = Comparative Fit Index; TFI = Tucker-Lewis Index; SRMR = Standardized root mean square residual

Other Measures

The other measures in this study were then examined for construct validity. See Table 20 for descriptive statistics for all scales used in this study and Table 21 for academic outcomes.

Table 20. Reliability of Scales from Study 2

Item	***n* items**	***α***	***M***	***Std Dev***
Biodata Measure				
General Parent/Family Influence and Support	8	.830	3.041	0.915
Receipt of STEM Knowledge or Experiences	7	.637	2.631	0.711
Extracurricular Math Com & Activities	7	.938	2.162	1.083
Proactive & Voluntary STEM-Seeking Behavior	6	.840	2.277	0.886
Parental Statements of Support for STEM	5	.897	2.513	1.247
Skill and Helpfulness of Teachers	5	.715	3.479	0.704
Extracurricular Science Com & Activities	7	.832	2.335	0.954
Self-Efficacy				
Math Self-Efficacy	8	.777	3.636	0.641
Science Self-Efficacy	10	.907	3.428	0.782
STEM Major Self-Efficacy[a]	9	.891	4.869	2.196
General Self-Efficacy	9	.898	3.408	0.626
Interest				
Task Interest	8	.908	2.412	1.092
Math Interest	7	.939	2.111	1.024
Intrinsic Career Interest	4	.697	3.874	0.649
Career Outcome Expectancies				
Math	6	.833	2.875	0.908
Science	6	.937	3.575	1.195
STEM Career Plans	4	.969	3.372	1.372
Proactivity	10	.923	3.379	0.801

Note. *N = 170.* All scales, unless otherwise specified, are on a 5-point Likert scale. [a]10-point Likert scale

Table 21. Academic Preparation and Outcomes for Study 2

Item	***N***	***M***	***Std Dev***
High School STEM Preparation			
STEM AP Credit Hours[a]	170	11.40	9.774
Math ACT Score[b]	112	32.57	3.959
Math SAT Score	142	750.07	60.489
First-Semester GPA			
First-Semester STEM GPA	136	3.326	0.611
First-Semester Overall GPA	170	3.579	0.409
Number of STEM Courses Taken	136	2.380	1.152

Note. [a]Generally 3-4 credits are transferred per class tested out of via AP credits; in some cases, a 5 AP score allows two classes to tested out of, meaning 6-8 credit hours are granted. [b]ACT Math scores were transformed to SAT Math scores using ACT's conversion table to ensure every participant had math standardized test data for the SEM

As with Study 1, I then examined subgroup differences in biodata factors. Using planned contrasts, I compared White students to underrepresented minority (Black and Hispanic) students. White students reported significantly greater general parent support *(F(*1,165) = 6.271, p = .013) and proactive and voluntary STEM behavior *(F(*1,165) = 8.496, p = .004) than underrepresented minority students. White students were also marginally more likely to report higher STEM knowledge and experiences (p = .088), lower parental support for STEM (p = .060), and higher participation in science competition and activities (p = .073). See Table 22 for the means of all biodata factors by race.

Table 22. Biodata Factor Means by Race

	Race				
Biodata Factor	Asian American	Black or African American	Hispanic or Latinx	White or Caucasian	Multi-racial/ Other
General Parent/Family Influence and Support	3.14 (0.75)	3.23 (0.95)	2.16 (0.85)	3.19 (1.00)	3.25 (0.84)
Receipt of STEM Knowledge or Experiences	2.70 (0.67)	2.65 (0.80)	2.24 (0.57)	2.71 (0.75)	2.53 (0.46)
Extracurricular Math Com & Activities	2.44 (1.07)	2.17 (1.25)	1.34 (0.58)	2.12 (1.09)	1.88 (0.99)
Proactive & Voluntary STEM-Seeking Behavior	2.36 (0.82)	2.07 (0.83)	1.76 (0.86)	2.48 (0.97)	2.08 (0.58)
Parental Statements of Support for STEM	3.05 (1.09)	2.76 (1.34)	2.18 (1.20)	1.97 (1.19)	1.90 (1.08)
Skill and Helpfulness of Teachers	3.32 (0.63)	3.63 (0.75)	3.63 (0.64)	3.59 (0.79)	3.59 (0.70)
Extracurricular Science Com & Activities	2.50 (1.02)	1.93 (0.79)	2.12 (0.87)	2.42 (0.95)	2.10 (0.99)

Note. *N = 170.* All scales are on a 5-point Likert scale, *SD* in parentheses

Next, I examined gender differences and found two significant differences in formative experiences by gender. First, male students tended to report more proactive and voluntary behavior toward STEM than female students ($t(168) = 2.050$, $p = .042$). Second, males reported greater participation in extracurricular science competitions and activities ($t(168) = 2.632$, $p = .009$). No other significant gender effects were found among the biodata factors. See Table 23 for the means of all biodata factors by gender.

Table 23. Biodata Factor Means by Gender

	Gender		Test of Mean Differences	
Biodata Factor	Female	Male	*t*	*p*
General Parent/Family Influence and Support	3.08 (0.95)	3.05 (0.87)	0.238	.812
Receipt of STEM Knowledge or Experiences	2.59 (0.69)	2.71 (0.71)	1.080	.282
Extracurricular Math Comp & Activities	2.08 (1.05)	2.29 (1.14)	1.181	.239
Proactive & Voluntary STEM-Seeking Behavior	2.18 (0.85)	2.47 (0.92)	2.050*	.042
Parental Statements of Support for STEM	2.54 (1.25)	2.44 (1.26)	0.114	.608
Skill and Helpfulness of Teachers	3.45 (0.71)	3.56 (0.70)	0.958	.339
Extracurricular Science Comp & Activities	2.20 (0.90)	2.61 (1.04)	2.632**	.009

Note. Degrees of freedom = 168. * < *.05,* ** < *.01, SD* in parentheses

I then examined biodata factor intercorrelations and found that the general parent support factor had low to non-significant correlations with all other factors, indicating that this might be a distinct construct. Similarly, intercorrelations were low or non-significant for teacher support and for parental support for STEM. The largest correlations were between STEM knowledge and experiences and voluntary STEM behavior (r = .698) and science competitions and voluntary STEM behavior (r = .600). Other large correlations were found between STEM knowledge and both math competitions (r = .446), and science competitions (r = .546). Math competitions were also correlated with both voluntary STEM behavior (r = .493) and science competitions (r = .516). See Table 24 for intercorrelations of the seven biodata factors.

Table 24. Study 2 Intercorrelations of Biodata Factors

	Biodata Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	General Parent/Family Influence and Support	*(.830)*						
2	Receipt of STEM Knowledge or Experiences	.289**	*(.637)*					
3	Extracurricular Math Competitions & Activities	.099	.446**	*(.938)*				

	Biodata Factor	1	2	3	4	5	6	7
4	Proactive & Voluntary STEM-Seeking Behavior	.172*	.698**	.493**	*(.840)*			
5	Parental Statements of Support for STEM	.188*	.386**	.304**	.314**	*(.897)*		
6	Skill and Helpfulness of Teachers	.198**	.192*	.009	.072	-.117	*(.715)*	
7	Extracurricular Science Competitions & Activities	.158*	.546**	.516**	.600**	.266**	.080	*(.832)*

Note. $N = 170$. Reliability estimates are calculated as Cronbach's alpha (Cronbach, 1951) in parentheses on the diagonal. * < *.05*, ** < *.01*

Four of the biodata factors – STEM knowledge, math competitions, proactive behavior, and science competitions – had consistent small to medium correlations with all four self-efficacy measures. The largest correlations were between proactive STEM behavior and science self-efficacy ($r = .428$) and STEM knowledge and science self-efficacy ($r = .399$). Conversely, correlations were non-significant between any types of self-efficacy and general parent support, STEM-specific parent support, or teacher support. Further, correlations were generally slightly larger between math, science, and STEM major self-efficacy than the broader general self-efficacy construct. See Table 25 for all correlations.

Table 25. Correlations of Biodata Factors with Self-Efficacy

	Biodata Factor	Math Self-Efficacy	Science Self-Efficacy	STEM Major Self-Efficacy
1	General Parent/Family Influence and Support	-.086	.045	-.026
2	Receipt of STEM Knowledge or Experiences	.184*	.399**	.311**
3	Extracurricular Math Competitions & Activities	.316**	.319**	.265**
4	Proactive & Voluntary STEM-Seeking Behavior	.254**	.428**	.337**
5	Parental Statements of Support for STEM	.006	.149*	.015
6	Skill and Helpfulness of Teachers	.050	.082	.116
7	Extracurricular Science Competitions & Activities	.190*	.323**	.206**

Note. N = 170 * < *.05*, ** < *.01*

Regarding the interest measures, correlations were primarily non-significant between general parent support, STEM-specific parent support, and teacher support and all of the interest measures. The strongest correlations were between proactive STEM behavior and math interest (r = .424) and proactive STEM behavior and task interest (r = .384). There were also medium correlations between STEM knowledge and task interest (r = .367) and math interest, (r = .299); math competitions and task interest (r = .275) and math interest (r = .364); and science competitions with task (r = .306) and math interest (r = .283). Proactivity had no significant correlations with any biodata factor besides a small positive correlation with proactive STEM behavior (r = .200). See Table 26 for all correlations.

Table 26. Correlations of Biodata Factors with Interest and Proactivity

	Biodata Factor	**Task Interest**	**Math Interest**	**Proactivity**
1	General Parent/Family Influence and Support	-.059	-.028	.045
2	Receipt of STEM Knowledge or Experiences	.367**	.299**	.078
3	Extracurricular Math Competitions & Activities	.275**	.364**	.126
4	Proactive & Voluntary STEM-Seeking Behavior	.384**	.424**	.200**
5	Parental Statements of Support for STEM	.143	.126	-.130
6	Skill and Helpfulness of Teachers	.148*	.076	.122
7	Extracurricular Science Competitions & Activities	.306**	.283**	.094

*Note: N = 170 * < .05, ** < .01*

Almost all biodata factors had small to medium positive correlations with both math and science career outcome expectancies, as well as with STEM career plans, with the largest correlations between voluntary STEM behavior and math career outcome expectancies (r = .360), science career outcome expectancies (r = .377), intrinsic career fulfillment (r = .228) and STEM career plans (r = .346). Correlations were also significant between STEM knowledge and

math career outcome expectancies (*r* = .375), science career outcome expectancies (*r* = .307), intrinsic career fulfillment (*r* = .149) and STEM career plans (*r* = .275). General parent support and teacher support had no or almost no significant correlations with any of the career outcome expectancies measures. For STEM career plans specifically, correlations were positive with STEM knowledge (*r* = .275), math competitions and activities (*r* = .177), proactive and voluntary STEM behavior (*r* = .346), parental support for STEM (*r* = .307), and extracurricular science competitions and activities (*r* = .190). Correlations were non-significant with teacher support and negative with general parental support (*r* = -.167). See Table 27 for all correlations.

Table 27. Correlations of Biodata Factors with Career Outcome Expectancies

	Biodata Factor	**Math COE**	**Science COE**	**Intrinsic Career Fulfillment**	**STEM Career Plans**
1	General Parent/Family Influence and Support	.067	-.108	-.005	-.167*
2	Receipt of STEM Knowledge or Experiences	.375**	.307**	.149*	.275**
3	Extracurricular Math Competitions & Activities	.273**	.184*	.144	.177*
4	Proactive & Voluntary STEM-Seeking Behavior	.360**	.377**	.228**	.346**
5	Parental Statements of Support for STEM	.242**	.283**	.084	.307**
6	Skill and Helpfulness of Teachers	.170*	-.056	.113	-.039
7	Extracurricular Science Competitions & Activities	.221**	.194**	.126	.190*

*Note. N = 170; COE = Career Outcome Expectancies * < .05, ** < .01.*

Examining objective academic outcomes, general parent support had no significant correlations with any academic outcome, nor did teacher support. STEM knowledge and experiences showed small correlations with all four academic outcomes, ranging from correlations of .198 (overall first semester GPA) to .206 (math standardized test scores). Other

small to medium correlations were found between extracurricular math activities and STEM AP credits (r = .230) and math standardized tests scores (r = .300). Parental statements of support for STEM predicted STEM AP credits in high school (r = .226) and students' math ACT/SAT scores (r = .277), but neither STEM GPA nor overall first-semester GPA. Both proactive STEM behavior and extracurricular science experiences predicted math ACT/SAT scores as well as STEM GPA (r = .199 for proactive behavior and r = .159 for extracurricular science experiences), but not overall GPA. The only predictor of number of STEM courses taken in students' first semester was general parent support, which was negative (r = -.302). See Table 28 for all correlations.

Table 28. Correlations of Biodata Factors with Academic Performance

	Biodata Factor	**STEM AP Credits**	**Math ACT/ SAT[a]**	**STEM First Semester GPA**	**Overall First Semester GPA**	**Num. STEM Courses Taken**
1	General Parent/Family Influence and Support	-.018	-.080	.050	.153*	-.302**
2	Receipt of STEM Knowledge or Experiences	.204**	.206**	.198*	.165*	.111
3	Extracurricular Math Competitions & Activities	.230**	.300**	.129	.093	-.002
4	Proactive & Voluntary STEM-Seeking Behavior	.160*	.199**	.166	.042	.112
5	Parental Statements of Support for STEM	.226**	.277**	.129	.111	.057
6	Skill and Helpfulness of Teachers	-.102	-.146	-.175	-.027	-.055
7	Extracurricular Science Competitions & Activities	.130	.159*	.172	.086	.141

*Note: N = 170. [a]ACT Math scores were transformed to SAT Math scores using ACT's conversion table * < .05, ** < .01*

Structural Equation Model

Using a structural equation model that incorporated the survey data and objective academic data, I evaluated whether the relationships between constructs followed those predicted by the SCCT model, and whether the biodata measure predicted second-semester college major and post-college career plans. I included STEM GPA for the fall, science and math AP courses taken in high school, and AP STEM credits transferred to Rice in the model, in addition to the survey items. In the model, I also allowed correlations between these variables, as well as math standardized test scores. The original model incorporated two to five observed variables for each of the seven constructs, meaning the model was based on 24 observed variables. See Figure 6 on page 84 for the model tested.

First, I ran the originally hypothesized structural equation model. It was a poor fit for the data (*CFI* = 0.781, *TLI* = 0.737, *RMSEA* = 0.094). I then trimmed this model and excluded the three non-significant paths: 1) the teacher biodata factor, 2) science and math AP classes taken, and 3) Fall 2019 STEM GPA. Although doing so improved the fit (*CFI* = 0.804, *TLI* = 0.767, *RMSE* = 0.093), it was still unacceptably low.

I examined the modification indices for insight into whether there might be a better way to model these data. I did not alter the path from the background experiences to formative experiences constructs, nor the path from initial major to intended major, with the perspective that retaining these paths was essential to capturing the basic premise of the SCCT model. In other words, only the relationships among interest, self-efficacy, and career outcome expectancies were explored for modification. The modification indices showed many significant relationships between science interest and science career expectations; math interest and math career expectations, and STEM career outcome expectations and STEM career interest,

suggesting that interest in math and science might be closely related to distinct math and science career outcome expectancies, respectively. Math and science self-efficacy also appeared to be two distinct constructs, both from the other factors and from each other.

Allowing correlations between science interest and science career with the more general STEM career factor, as well as between math interest and math career and the more general STEM career factor, but not allowing science and math variables to correlate produced a model that approached an acceptable fit (*CFI* = 0.870, *TLI* = 0.838, *RMSEA* = 0.089). After removing the non-significant path of Fall 2019 STEM GPA, the fit met the general minimum criterion for acceptable model fit (*CFI* = 0.902, *TLI* = 0.870, *RMSEA* = 0.080). Finally, due to the evidence that math and science self-efficacy were distinct constructs in the model, but with the perspective that it still made conceptual sense that these constructs would correlate, as well as that math interest and career plans would correlate with science interest and career plans, I allowed these two paths to correlate, which improved the model fit (*CFI* = 0.930, *TLI* = 0.914, *RMSEA* = 0.065). Addressing Research Questions 1 and 2, all biodata factors except the teacher support factor significantly contributed to the model. Fall 2019 STEM GPA was also non-significant. Counter to my expectations, adding students' satisfaction with their previous semester's grades as a mediator between initial and intended major slightly decreased the fit of the model, as did adding students' perceptions of the effort they put forth over the previous semester, so both variables were excluded in the final model. All these changes were the extent to which theoretical rationale seemed appropriate to justify changing the originally proposed model to this refined model. The final model, with standardized paths, is shown in Figure 7.

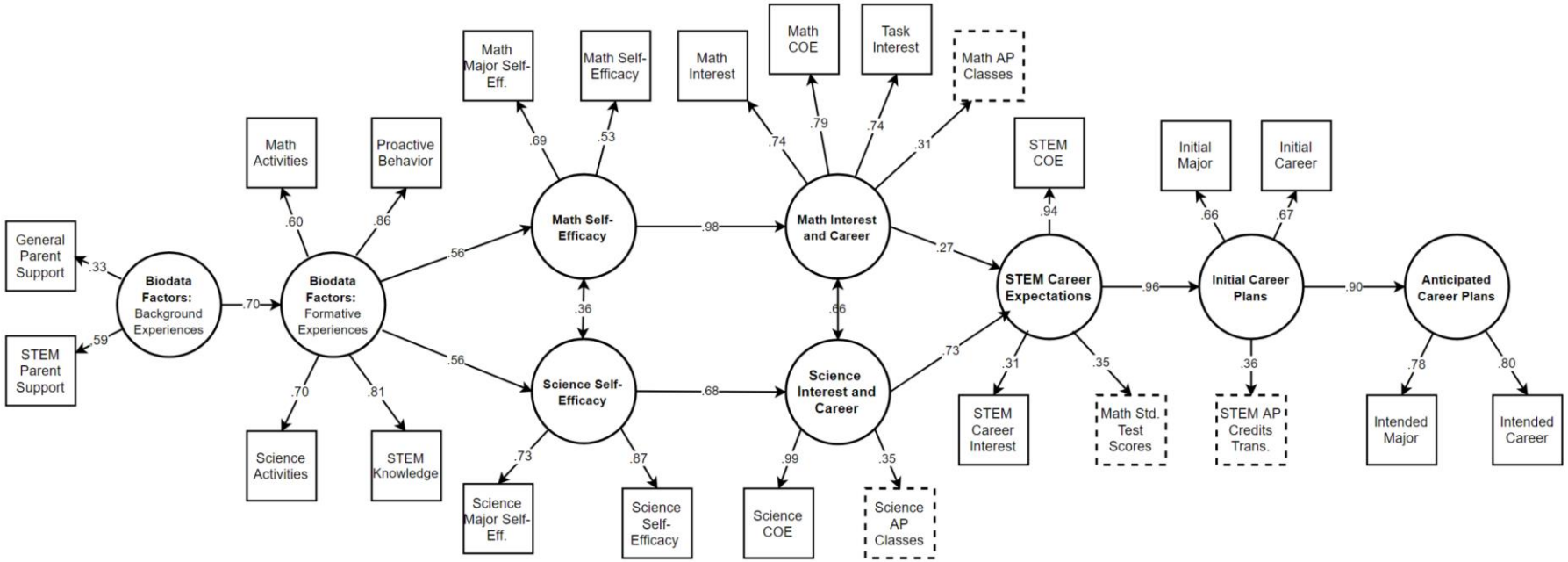

Figure 7. Modified structural equation model with significant standardized paths; dash-bordered boxes represent academic data

Discussion

Results from the confirmatory factor analysis indicated acceptable but not high fit for the factor structure of the biodata measure, after certain items were eliminated due to misleading item content or by demonstrating low factor loadings in both Study 1 and Study 2. All findings are exploratory. Broadly speaking, the general parent support and the teacher support factors loaded most cleanly onto their hypothesized factor structures, followed by the parent support of STEM factors, which also had generally high loadings for most items. The parent-child relationship seemed to be more interrelated than many students in the original interviews that informed item development seemed to articulate or may have even realized (Bradford, 2018). For example, there were considerable cross loadings on many items in the voluntary behaviors and parents' supporting STEM factors. Parents might support STEM in response to students' behaviors or interests, and/or students who voluntarily participated in a science or math activity may also have been heavily influenced by their parents to pursue this interest.

In terms of the impact of teacher support, most items loaded cleanly onto this factor. After reviewing the items with high modification indices (see Table 18) and finding certain negative correlations between the teacher and parental support factors, it appears that students in this sample used their teachers for support if they did not have strong parental encouragement, meaning that the positive effect of teacher support and encouragement was not additive but compensatory in teachers' abilities to replace insufficient support or encouragement by parents. Whether or not this relationship holds true in other samples should be further studied.

The math competitions and activities factor showed cross-loadings with the science competitions and activities factor, although the model was still a better fit when the two were considered separate constructs. Students who look forward to math extracurricular activities and

participate in math competitions are not necessarily the same students who look forward to science extracurricular activities and participate in science competitions and science fairs, but a student high in one of these constructs is likely relatively high in the other.

Finally, students' STEM knowledge and their voluntary or proactive behavior did not load cleanly for many items. However, combining these two factors did not produce a better fit for the data, indicating that two distinct factors exist for these items in this sample. Because all items in both studies were drawn from qualitative data provided by successful STEM students, it may be worth further exploring these items and constructs in future studies in order to ascertain whether there are other constructs or factor structures that may be able to better capture these items, as they may be important in predicting relevant academic or psychological outcomes.

Certain biodata factors showed subgroup differences by race or gender. Echoing a finding from Study 1, White students reported greater general parent support than underrepresented minority students, perhaps indicating differences in parents' knowledge of elementary school education or perspectives regarding their role in their children's academic lives. White students also reported behaving more proactively regarding obtaining STEM experiences in elementary school. This behavioral tendency may be facilitated by White students' familiarity and comfort communicating and participating in science and math domains (such as science presentations or museum visits) that were likely majority White or Asian American. The same mechanisms that create additional barriers for underrepresented minority students in school settings likely extend to non-classroom settings. White students were also marginally more likely to report greater STEM knowledge and experiences and participation in science competitions and activities, perhaps as a result of the same additional barriers underrepresented minority students face when behaving proactively or seeking out STEM experiences. Interestingly, White students were less

likely to report that their parents encouraged them to pursue STEM interests or careers specifically, replicating a finding in Study 1. As previously discussed, underrepresented minority parents might place a higher priority on their children working in STEM careers, perhaps because they view these careers as well-paying and/or reliable (which the content of several of the biodata items for this factor addressed) in a job world that might create additional barriers for underrepresented minority students.

Regarding gender differences, male students tended to report more proactive behavior toward STEM than female students, a difference that favors the majority group, just as White students reported more proactive behavior than underrepresented minority students. Male students may be more comfortable operating in math and science domains than female students, due to factors mentioned in Chapter 2, such as a tendency for science and math textbooks to emphasize the contributions of male scientists and mathematicians and to use traditional masculine interests when providing examples. Second, males reported greater participation in extracurricular science competitions and activities, which reflects findings in the literature that female students often have less access to science equipment, as well as tending to find fewer science activities that interest them. No other biodata factors differed as a function of gender.

I also examined correlations between individual biodata factors and other constructs captured in this study. Four of the biodata factors consistently predicted math, science, and math and science major self-efficacy: STEM knowledge, proactive behavior, and science and math competitions. All four of these factors represent generally active experiences, in contrast to the more passive factors of general and STEM-specific parental support and teacher support. Having these experiences and the opportunities to interact with and learn directly from these experiences while students were young may have influenced their trajectories and led to higher STEM self-

efficacy in college. Parents' support of STEM significantly predicted only science self-efficacy, indicating that students may develop their math and STEM major self-efficacy through other routes than parental influence, and parents may be able to bolster their children's beliefs about their ability to succeed in science topics in a way they are not able to affect their children's math or major self-efficacy.

The same four biodata factors – STEM knowledge, proactive behavior, and science and math competitions – all had significant small to medium correlations with math and task interest. This may be a reciprocal relationship, in which participating in these activities increases interest, which increases students' chances of participating in these activities, or it may be directional, in which interest drives subsequent behavior or vice-versa. As with self-efficacy, parents and teachers do not seem to have a direct impact on children's STEM interests, indicating that active behaviors by children (the biodata factors more relevant to the SCCT formative experiences construct) are more important predictors of students' interest, rather than background experiences factors. These same factors, in addition to parental support of STEM, appeared to drive many of the STEM career outcome expectancies variables, including math and science career outcome expectancies, STEM career plans, and intrinsic career fulfillment. STEM knowledge and proactive behavior in particular positively predicted all four outcomes. These were also the only two factors that predicted intrinsic career fulfillment, which was a measure consisting of the items most relevant to having a STEM career and the degree to which students valued those items in their future career. Conversely, although parental STEM support, science competitions, and math competitions significantly correlated with science, math, and more general STEM career outcome expectancies, they did not correlate with students preferring the

job values and activities of most STEM jobs. Students who are high in proactive STEM behavior and STEM knowledge may be those who are most suited for STEM careers.

I also examined correlations between biodata factors and objective academic outcomes. From the perspective of STEM first-semester GPA being the most distal and domain specific academic outcome available, STEM knowledge and experiences (with science competitions and proactive behavior marginally correlated) may be the factor(s) most worth exploring. Although it seems rational that students who gain greater STEM knowledge will have a higher STEM GPA, the mechanism by which this is accomplished is less clear, as well as why science activities but not math activities might marginally predict higher STEM GPAs, or why parent support for STEM does not predict higher STEM GPAs or number of STEM classes taken during students' first semester in college. Further, having general parent support seemed to come at the expense of the number of STEM classes taken. Perhaps students who do not have a high intrinsic interest in STEM and also do not perceive parental pressure to engage in STEM are less likely to take STEM courses than students who have low intrinsic interest but received strong parental messages of support for STEM. As previously discussed, relying on teachers for support may indicate limited parental support or resources at home, which contribute to a negative relationship between perceived teacher support and all STEM objective academic outcomes.

Next, I tested the proposed structural equation model, using the refined scale and the originally proposed structure. The original model provided unacceptable fit; however, several changes that made theoretical and rational sense contributed to a much improved fit. Notably, science self-efficacy and math self-efficacy appeared to be distinct constructs, as did science interest and career plans and math interest and career plans. More general career interests and STEM career plans were also found to be a distinct construct, following science and math

interest. The different order and structure of this model compared to the original SCCT model (in which self-efficacy and career outcome expectations together precede interest, which precede career outcome expectations) may be due to the fact that this sample's students, self-efficacy, interest, and career plans had already changed as a result of their college experiences. Students also appeared to consider their math domain interest similarly to their math career interests, and the same pattern was found for science domain interest and science career interest. In other words, the distinction predicted by the SCCT model of STEM career outcome expectations preceding STEM interest was not supported in this sample. Instead, these appeared to be the same construct. Conversely, science and math constructs appeared to be distinct from each other. Additional research should explore whether this distinction can be replicated on other samples.

Six of the seven biodata factors contributed significantly to the model, with only teacher support showing a positive but not significant path. These findings are promising in terms of the fact that although the biodata measure would benefit from further development, in its current form it was nevertheless significant in a path analysis that culminated in outcomes as distal as students' second semester intended college major and career.

Most of the relationships among objective academic outcomes and other variables were significant in this model, including AP math and science classes taken in high school correlating with math interest and science interest, respectively; math standardized tests correlating with STEM career interest and outcome expectations; and STEM credits transferred to Rice correlating with students' initial major. Interestingly, the only objective academic outcome that did not correlate with either initial major or intended major was students' first-semester STEM GPA (nor was it explained by students' satisfaction with their grades or their perceived course effort). Perhaps students did not interpret their GPA after only one semester as providing

meaningful information to drive decisions about their major, or factors other than GPA that this study did not capture drove students' decisions about their major.

Taken together, the results from the refined structural equation model suggest that science and math interest, self-efficacy, and other constructs integral to the SCCT model should be considered separately. These results also support one of the major findings in Study 1, that math and science competitions and extracurricular activities were conceptually distinct (and were thus included as distinct factors in Study 2). The refined model also suggests that students' career intentions develop as a result of their math and science domain and career interests, rather than their career outcome expectancies influencing students' interests. Future research should include at least one more study to confirm the findings of this study, including both the biodata scale's factor structure and the structural equation model describing the relationships in the SCCT model. Because Rice students are generally high-performing students, they are not a random sample of the US student population, and range restriction is likely. Future studies should also delineate between math and science constructs and further explore directionality of the path model on other samples. Overall, although the fit of this model is not extremely high, the current model nevertheless serves as an important exploratory first step and does appear to represent the data in a theoretically meaningful and interpretable way.

CHAPTER 6: DISCUSSION

Over the course of the previous two studies (as well as during the preliminary stages of the biodata measure development discussed in Chapter 3; Bradford, 2018), I 1) developed and refined over several iterations a biodata measure of STEM formative experiences, 2) examined the convergent and discriminant validity of the proposed factors, 3) conducted exploratory and confirmatory factor analyses on these data, and 4) explored the fit of a structural equation model to the theoretical framework guided by social cognitive career theory (Lent et al., 1994).

Summary of Findings

The following hypotheses were examined in Study 1.

Hypothesis 1: The biodata measure will demonstrate moderate (approximately *r* = .30) convergent validity with openness to experience.

As expected based on the research linking openness to experience and the investigative vocational interest to STEM outcomes, students who had more STEM-related experiences and more opportunities to learn about STEM tended to have greater openness to experience, supporting Hypothesis 1.

Hypothesis 2: The biodata measure will demonstrate discriminant validity with agreeableness.

Hypothesis 2 was not supported, as many significant relationships between biodata factors and agreeableness were found. For example, students who participated in math competitions were more likely to be extraverted and agreeable, students who perceived favorable experiences with their teachers were more likely to be extraverted and agreeable, and students who participated in science competitions and activities were more likely to be agreeable and neurotic.

Hypothesis 3: The "Proactive Behavior" biodata factor will demonstrate moderate convergent validity with proactivity.

Hypothesis 3 was supported. Proactivity had significant with both the expected proactive and voluntary behavior factor, as well as with STEM knowledge and experiences, extracurricular math activities, parental support of STEM, and teacher support

Hypothesis 4: The "Encouragement and Exposure to STEM" and "Receiving Help in School Settings" factors will demonstrate moderate convergent validity with school quality, teacher helpfulness, and book availability.

Hypothesis 4 was generally supported, with the caveat that the factor structure had changed slightly as a result of the exploratory factor analysis. Educational opportunities showed several meaningful correlations with biodata factors. Participating in extracurricular science activities (which, as previously discussed, may be opportunities only students from higher resourced schools have access to) had a medium correlation with higher school quality. Further, the general parental influence factor showed a medium-sized positive correlation with students' availability of books. Parents who play a more active role in students' academic performance may also be more likely to provide their children access to books.

Hypothesis 5: The biodata measure will demonstrate discriminant validity with the number of elementary schools that students attended.

The number of schools attended (which was presumably outside students' control and thus should not impact students' behavior) did not have significant correlations with any other biodata factor besides perceived teacher support or helpfulness, generally supporting Hypothesis 5. The significant relationship with teacher support may be the result of students who changed

schools needing to rely on their teachers more to orient themselves to a new school and learn new material.

Hypothesis 6: The data will show evidence of six distinct factors (Exposure and Encouragement for STEM, Being Provided STEM Resources, Having Hands-on STEM Experiences, Participating in STEM Competitions, Receiving Help on School Assignments, and Proactive or Voluntary STEM Behaviors), with individual items loading onto the a priori anticipated factors.

Hypothesis 6 was not supported. I ran a confirmatory factor analysis to determine whether the biodata items loaded onto the expected six factors and found that this model did not show acceptable fit. I then conducted an exploratory factor analysis on the data and found a seven-factor solution to test in Study 2. These factors comprised three background influence factors: general parent support, STEM parent support, and teacher support; and four formative experience factors: math extracurricular activities and competitions, science extracurricular activities and competitions, proactive behavior, and STEM knowledge.

The following research questions were explored in Study 2.

Research Question 1: Which background influence themes predict students' second-semester major?

I examined second-semester STEM major and career intentions as the most distal outcome in the model. Of the three background experience factors, only parental support for STEM predicted future major and career plans. Correlations were non-significant with teacher support and negative with general parental support (perhaps because parents provided students greater opportunities to explore non-STEM interests).

Research Question 2: Which formative experience themes predict students' second-semester major?

All four STEM formative experiences positively predicted students' STEM major and career plans: STEM knowledge, math competitions and activities, proactive and voluntary STEM behavior, and extracurricular science competitions and activities. The impact of having certain STEM experiences or behaviors in elementary school appears to persist into college.

Research Question 3: How well do the data obtained from the surveys and students' academic records fit the proposed model based on social cognitive career theory?

A confirmatory factor analysis showed a low fit with the full biodata measure. I then examined the modification indices for items that did not load highly onto the a priori proposed factors. Fifteen of the items had high modification indices that indicated unanticipated loading onto latent factors other than the ones I proposed, and six of these items were similar or identical to items with high modification indices in Study 1. The remaining items appeared to be a result of shifting construct definitions as the factor structure evolved from the original six-factor model to the seven-factor model. Specifically, several items hypothesized to represent parental support for STEM and items designed to represent general parental support had high cross-loadings onto the other factor. Using the modified version of the scale, I ran a confirmatory factor analysis to determine how well the data fit the new scale, which showed acceptable fit for the data.

Then, using a structural equation model with the modified survey and objective academic data, I evaluated whether the relationships between constructs followed the paths predicted by the SCCT model, and whether the biodata measure predicted second-semester college major and post-college career plans. However, the fit was again unacceptably low. I examined the

modification indices for insight into whether there might be a better way to model these data. The modification indices showed significant relationships between science interest and science career expectations; math interest and math career expectations; and STEM career outcome expectations and STEM career interest, suggesting that interest in math and science might be closely related to distinct math and science career outcome expectancies, respectively. Math and science self-efficacy also appeared to be two distinct constructs, both from the other factors and from each other. Using the modified version of the scale, I ran a confirmatory factor analysis to determine how well the data fit the new scale. The modified model showed acceptable fit for the data, and all biodata factors except the teacher support factor significantly contributed to the model.

Contributions

Contributions to Research

Using social cognitive career theory as a theoretical framework, this study involved the development of a biodata measure and established its validity in a structural equation model testing the theory. This research connects psychosocial theory via an established framework with biodata research and measure development in a way that has not been done before to my knowledge. The biodata measure, as a retrospective data collection technique that asked students to recollect their experiences as far back as a decade previously, inherently produced bias and subjectivity as students relied on their memories to answer the items. However, despite any historical inaccuracies in students' responses, the measure nevertheless predicted important outcomes in college, indicating that objective data collection may not be required to study early STEM experiences (although objective or longitudinal data collection would be worth exploring, as well). I also conducted factor analyses of the biodata items, which offers insight into

important constructs that influence long-term STEM outcomes. Across both studies, I found that students received encouragement and resources that were both general and STEM-specific from their parents, that participating in both competitive and non-competitive math and science activities was influential, and that students varied in the degree to which they sought out science and math activities, as well as the amount of knowledge they had on science and math topics in elementary school. In Study 2, the modified structural equation model showed a different path between biodata factors and the career and major trajectories of students in college than previously hypothesized based on the social cognitive career framework. Perhaps most interesting in the modified model is that STEM constructs might be more accurately delineated between those that are science-specific and those that are math-specific. Although both contributed to the model, they also appeared to be conceptually distinct. Certain factors also showed evidence of differing as a function of race and gender. Overall, this research might guide future STEM education research by demonstrating that broader educational theories (albeit with slight adaptations) might accurately predict STEM-specific student outcomes, encouraging researchers to more explicitly incorporate theoretical rationale into their research designs, and suggesting that it might be valuable to use distinct science and math measures and to report science and math outcomes separately.

Contributions to Practice

The biodata questionnaire developed in this study might ultimately be used to capture the STEM experiences of a sample of students, whether at the group level to draw broad conclusions about that sample's STEM experiences or to identify respondents with high or low ratings on certain factors or on the biodata measure as a whole. However, the measure should first undergo at least one more round of refinement in an additional study (discussed in the following section).

Findings from this study on specific biodata constructs, although preliminary, also have important practical implications. For example, conceptualizing science and math experiences as distinct may be valuable for practitioners, because both science extracurricular activities and competitions and math extracurricular activities and competitions appear to have roles in predicting later STEM outcomes, but these are not always the same outcomes. Schools, parents, and teachers might have a stronger long-term impact on students' STEM outcomes if they provide both types of experiences. Parental support for STEM also played a significant role in many STEM outcomes. Children appear to perceive their parents' expectations for them to pursue STEM, even at a young age, and some students may change their behaviors accordingly. Finally, proactive and voluntary STEM behavior had consistent correlations with many long-term STEM outcomes. Although proactive behavior may to some extent reflect a stable personality trait, students who are provided access to STEM opportunities they find interesting might proactively participate in those activities, which may increase these students' likelihood of increasing their STEM interest or developing STEM major or career outcome expectancies. Taken cumulatively, these findings (if they are replicated in a future study) might guide decision makers toward where their efforts might be most effective, as well as provide insight into factors that are especially likely to produce gender or race biases. These arenas might include the development of parent interventions (e.g. providing parents information on STEM careers), new school curricula (e.g. offering a broader array of science and math material to capture students' interest), and teacher training (e.g. helping teachers incorporate science experiments in their classroom), as well as where school resources might be best directed (e.g. placing a priority on purchasing science equipment).

Future Research

A future Study 3 would be a valuable next step in this research. This study would include 1) further item refinement and 2) scale validation via a confirmatory factor analysis to determine an appropriate factor structure for the items that have shown significant cross loadings and understand the distinct constructs items are capturing. Regarding item refinement, the STEM knowledge and proactive behaviors factors in particular would benefit from further exploration to determine the underlying constructs that make them unique (or conversely, the underlying construct that links them together), and drive item refinement. Table 18 lists proposed changes to the items that demonstrated high modification indices in Study 2 and that may be useful to refine the biodata measure in a future Study 3.

In a confirmatory factor analysis, the impact of teachers may be especially important to explore, in terms of whether teachers contribute positively to student STEM outcomes, or whether, as findings from Study 2 suggest, the primary benefit of high quality and supportive teachers is compensatory, in that it helps the students who receive the least amount of parental support and STEM experiences at home. Whether the teacher biodata factor continues to be non-significant in structural equation models on different samples is worth exploring, as well as the mechanics and circumstances teachers under which play the biggest role on students' long-term general and STEM college outcomes. Study 3 might explore whether it makes sense to continue using this biodata factor even if it is a distinct construct (which Study 1 and Study 2 generally seem to support) if it does not contribute meaningfully in a path analysis to any outcomes of interest. Study 3 might also provide insight into whether considering math and science constructs to be distinct factors continues to be the best fit for the data provided by other samples. Both Study 1 and Study 2 indicated that students experience math and science differently, and these

experiences, although very similar in structure (such as a science competition versus a math competition), may have different impacts on students' STEM interests, career plans, and eventual college major choices. Study 3, which might test a modified version of the SCCT model with math and science factors explored separately, would contribute to a better understanding of the unique role each STEM domain plays. Another benefit of Study 3 might be in testing the model on non-Rice students, such as students at a public university (e.g. the University of Houston), or community college students, to determine whether the findings from Study 2 will be applicable to a broader sample of students.

More broadly, future longitudinal studies might be able to better capture pre-college self-efficacy, interest, and career plans and then track students' later college major decisions, rather than collecting all these variables at a single point in time. Although this research used retrospective data for early life experiences, it would have been impractical to ask participants to respond to certain other items, such as self-efficacy, as if they had still been in high school (or even younger). As a result, self-efficacy, interest, career plans, and intended major were all representative of students' perceptions as they completed the survey at a single point in time. Future studies that collect data during at least two different time points would allow for more nuanced analyses of the model paths.

Study Limitations

Although a strength of this study is in having a sample of students who had a wide range of STEM preparation levels, STEM interest, and career plans, these were nevertheless all students who had performed well enough in high school to be offered admission to Rice, a highly selective institution, making range restriction in both Study 1 and Study 2 plausible. Rice students might differ significantly on many factors and measures in this study from a broader

sample of students, including possibly having higher levels of parental support, access to resources, and quality of education than students at less selective universities. For instance, the true relationship between first-year college students' general parental support in elementary school and performance in college might be larger than Study 2 found, but because Rice students tended to report a relatively high level of general parental support, the correlation between these constructs might have been attenuated due to range restriction (i.e. few Rice students reported low levels of general parental support). Further, results from both the confirmatory factor analysis and the structural equation model should be considered preliminary until they can be validated in Study 3 and other follow-up studies. Confirmatory factor analysis findings and modification indices were used to reduce items from the original full biodata measure. Many items also had high cross-loadings in Study 1, and most other problematic items appeared to be result of changes from the original six-factor to the new seven-factor solution and thus made rational sense to exclude; however, these were nevertheless post-hoc changes. Further, refinement and discussion of the structural equation model also involved making several post-hoc modifications after examining the modification indices of the original model. However, these changes largely involved separating math and science factors into distinct constructs, which makes rational and theoretical sense. Nevertheless, an *a priori* model should be tested with science and math factors as distinct constructs in future studies to determine whether these relationships hold true for other samples. Finally, all survey responses were captured at a single point in time, potentially impacting the fit of these data to the original model, which proposes self-efficacy and career outcome expectancies as largely occurring before college.

Conclusion

Together, these studies provided preliminary evidence for the validity of a new biodata measure scale, and then incorporated the updated biodata measure into a structural equation model to test the paths predicted by SCCT. Study 1 involved conducting an exploratory factor analysis and refining the biodata factor structure. In Study 2, a confirmatory factor analysis led to a refined version of the biodata measure, which was then incorporated into a structural equation model. Both studies provided insight into students' early experiences and ultimate college outcomes, from being exposed at an early age to STEM, to pursuing one or more STEM interests, to ultimately to deciding whether to major in STEM at the end of their freshman year of college. Overall, these studies provided evidence for the impact of formative experiences and background experiences in STEM education and on STEM outcomes, a line of research that clearly warrants further exploration.

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APPENDIX A

Preliminary Biodata Scale Before Initial Assessment

When you were elementary school age (11 and younger)...

Background Influences

1. Exposure to STEM: Experiences in which students attended or participated in activities about a STEM topic, major, or career path or interacted with people doing STEM research, studying STEM, or working in STEM careers.
    a. Events
        1. How often did you attend science, math, or engineering shows or demonstrations?
        2. How often did you participate in special science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?
        3. How often did you attend STEM activities that exceeded one day, such as STEM-related summer camps?
        4. How likely were you to attend or participate in STEM events that were voluntary?
        5. To what extent did your parents support you in participating in STEM activities?
        6. To what extent did your parents to communicate that it was more important for you to attend STEM events or activities than non-STEM activities?
        7. How likely were you to seek out information on STEM events you wanted to attend?
    b. People
        1. To what extent do you have parents, siblings, or extended family who worked in a STEM career?
        2. How often did you interact with adults in STEM fields who were not related to you?
        3. How often did you talk to siblings or cousins who were studying STEM in high school or college?
        4. How often did adults in STEM careers tell you about their career?
        5. How often did adults in STEM careers tell you to consider working in their career?
2. Encouragement for STEM: Experiences in which students perceived favorable messages from family, teachers or others regarding their ability to do STEM or their future major or career prospects in STEM.
    a. Encouragement for General STEM Interest
        1. To what extent did your parents encourage you to pursue a science, math, or engineering interest?
        2. To what extent did your parents encourage you to pursue STEM at the expense of your non-STEM interests?

3. To what extent did your parents encourage you to follow your passion or interests, regardless of whether they were STEM or non-STEM? (RC)
4. How often did teachers encourage you to work in science, engineering, or math when you graduated?
5. How often did your parents or teachers give you STEM-related books, toys, or other STEM gifts?
6. To what extent did your parents encourage you to pursue a STEM interest due to your innate talent or ability for the topic?
7. How often did your parents talk to you about taking STEM classes or choosing a STEM major in college?

b. Encouragement for Specific STEM Career

1. To what extent did your parents encourage you to work in a specific STEM career because that career had high income potential?
2. To what extent did your parents encourage you to work in a specific STEM career because that career would have jobs available or job stability?
3. How often did your teachers encourage you to work in a specific STEM career?
4. To what extent did your family provide you with resources, such as books or movies, about a certain STEM career path?
5. To what extent did your parents encourage you to work in a specific STEM career due to your innate talent or ability for that career?
6. How likely were you to tell your parents that you wanted to make your own career choices? (RC)
7. To what extent did your parents express no specific preference about you following a STEM versus non-STEM career? (RC)

Learning Experiences

1. Hands-on STEM Experiences: Experiences in which the student personally built or interacted with a STEM experiment, project, building, or other construction.

a. Self-Motivated Experiences

1. How likely were you to ask others for STEM-related gifts for your birthday or other holiday?
2. How often did you choose to work on hands-on STEM activities when you had the choice to do other activities?
3. How likely were you to work on hands-on STEM activities that were not required for school?
4. How likely were you to look forward to working on hands-on STEM activities in your classes?
5. How likely were you to ask your parents for parts or materials so you could work on hands-on STEM activities?
6. How likely were you to get bored of working on hands-on STEM activities? (RC)

b. Parent or Sibling Experiences

1. How often did your parents encourage you to work on STEM-related experiments or building projects?

2. How likely were your parents to provide you with the materials or instructions to work on STEM-related projects?
3. How likely were your parents to build or work on STEM projects with you?
4. How likely were your parents to help you on a hands-on STEM project when you needed help?
5. How often did your parents suggest new STEM hands-on activities for you to try?

2. STEM Competitions: Participation in competitive activities in which the student was tested in math or science topics.
    a. Math Competitions
        1. How often did you participate in math competitions?
        2. How likely were you to try your best at math competitions?
        3. How likely were you to look forward to math competitions?
        4. How likely were you to participate in math competitions that were voluntary?
        5. To what extent did your parents encourage you to participate in math competitions?
        6. To what extent did your parents encourage you to participate in math competitions?
    c. Science Competitions
        1. How often did you participate in science competitions?
        2. How likely were you to try your best at science competitions?
        3. How likely were you to look forward to science competitions?
        4. How likely were you to participate in science competitions that were voluntary?
        5. To what extent did your parents encourage you to participate in science competitions?
        6. To what extent did your teachers encourage you to participate in science competitions?
3. School Help Received: Students receiving individual help and/or encouragement from a teacher, parent, or sibling on completing school assignments.
    a. Help from Parents
        1. How often did your parents help you with your homework?
        2. How likely were your parents to ask you if you needed help with your homework?
        3. How helpful did you believe your parents would be if you had trouble with an assignment?
        4. How likely were you to ask your parents for school help if you needed it?
        5. How likely were you to try to figure out your assignments on your own rather than ask your parents for help? (RC)
    b. Help from Teachers
        1. How helpful did you believe that your teachers would be if you needed help with an assignment?
        2. How skilled did you believe your teachers were at teaching?

3. How often did your teachers encourage you specifically to do well in class?
4. To what extent did you believe your teachers prioritized helping other students over you? (RC)
5. How comfortable did you feel approaching your teacher with class questions?

APPENDIX B

Revised Biodata Scale after Initial Assessment

When you were elementary school age (11 and younger)...

Background Influences

1) Being Exposed or Encouraged for STEM

1. How often did adults in STEM careers tell you about their career?
2. How often did teachers encourage you to work in science, engineering, or math when you graduated?
3. To what extent did your parents encourage you to pursue a science, math, or engineering interest?
4. To what extent did your parents encourage you to pursue a STEM interest due to your innate talent or ability for the topic?
5. To what extent did your parents encourage you to pursue STEM at the expense of your non-STEM interests?
6. To what extent did your parents encourage you to work in a specific STEM career because that career had high income potential?
7. To what extent did your parents encourage you to work in a specific STEM career due to your innate talent or ability for that career?
8. What proportion of your parents, siblings, or extended family worked in a STEM career while you were growing up?
9. How close were you to siblings or cousins who were studying STEM in high school or college?
10. To what extent did your parents encourage you to work in a specific STEM career because that career would have plenty of jobs available?
11. To what extent did your parents say that they supported you in you participating in STEM activities?
12. How often did you talk to siblings or cousins who were studying STEM in high school or college about STEM topics?
13. How likely were you to be interested in a school topic if your parents did not encourage it? (RC)
14. To what extent did your parents encourage you to work in a specific STEM career because that career would have job security?
15. How often did your parents express a specific preference about your career choices?
16. To what extent did your parents encourage you to follow your passion or interests, regardless of whether they were STEM or non-STEM?
17. How often did your parents talk to you about the importance of taking science and math classes?
18. How often did your parents talk to you about the importance of choosing a STEM major in college?
19. How often did adults in STEM careers tell you that you would do well in a similar career?

20. How often did your teachers encourage you to work in a specific STEM career?
21. How often did you interact with adults in STEM fields who were not related to you?

2) Being Provided STEM Resources

1. To what extent did your parents provide financial support for you to participate in STEM activities?
2. How often did your parents or teachers give you STEM-related books, toys, or other STEM gifts?
3. How likely were your parents to provide you with the materials to work on STEM-related projects?
4. To what extent did your family provide you with books, movies, or TV shows about a certain STEM career path?
5. Were your parents more likely to pay for you to participate STEM activities than in non-STEM activities?
6. How often did your parents encourage you to work on STEM-related projects?
7. How willing were your parents to pay for new STEM activities for you to try?
8. How often did you attend multi-day STEM events, such as STEM-related summer camps?
9. How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?
10. How often did you attend one-day science, math, or engineering events, such as talks or demonstrations?

Learning Experiences

3) Having Hands-on STEM Experiences

1. How likely were you to get bored of working on mandatory hands-on STEM activities? (RC)
2. How much did you look forward to working on hands-on STEM activities in your classes?
3. How much did you generally prefer to work on hands-on STEM activities compared to other hobbies?
4. How often did you work on science experiments or projects in class?
5. How much access did you have to hands-on STEM materials at home?
6. How willing were your parents or other family members to pay for hands-on STEM project materials for you?
7. How often did you work on engineering, building, or construction projects in class?
8. How often did you work on science fair projects at school?
9. How often did you go on field trips to activities or places where you were able to touch or build things?
10. How often did you do hands-on math assignments, such as math blocks, puzzles, geometry projects, or filling in graphs or charts?

4) Participating in STEM Competitions

1. How likely were you to participate in math competitions that were voluntary?
2. How likely were you to participate in science competitions that were voluntary?
3. How likely were you to spend a lot of time after school preparing for math competitions?
4. How likely were you to spend a lot of time after school preparing for science competitions?
5. How much did you look forward to opportunities to participate in math competitions?
6. How much did you look forward to opportunities to participate in science competitions?
7. How often did you participate in math competitions?
8. How often did you participate in science competitions?
9. To what extent did your parents expect you to participate in science competitions?
10. To what extent did your teachers encourage you to participate in science competitions?

5) Receiving Help on School Assignments

1. How capable were your parents of helping you on a math assignment if you needed help?
2. How capable were your parents of helping you on a science assignment if you needed help?
3. How helpful were most of your teachers if you were struggling with an assignment?
4. How often did your parents help you study for tests?
5. How skilled were most of your teachers at explaining new topics to the class?
6. How helpful did you think your parents would be if you had trouble with an assignment?
7. How often did your parents ask you if you needed help with your homework?
8. How often did your teachers specifically encourage you in particular to do well in class?
9. To what extent did you believe your teachers prioritized helping other students over you? (RC)
10. To what extent did your parents expect you to figure out difficult class assignments on your own? (RC)

6) Proactive or Voluntary STEM Behaviors

1. How often did you choose to work on hands-on STEM activities (e.g. experiments, building projects, lab activities) after school when you had the choice to do other activities?
2. How likely were you to ask others for STEM-related gifts for your birthday or another holiday?
3. How likely were you to seek out information on STEM events you wanted to attend?
4. How likely were you to ask your parents for parts or materials so you could work on hands-on STEM activities?
5. How likely were you to choose to attend or participate in STEM events that were voluntary?
6. How likely were you to look up instructional videos or books to complete difficult assignments on your own?
7. How comfortable did you feel approaching your teacher with science or math questions after class?

8. How comfortable did you feel asking your teacher science or math questions during class?
9. How likely were you to ask your parents for help with a class assignment if you were struggling with it?
10. How likely were you to work on extracurricular or extra credit math assignments just because you wanted to?
11. How likely were you to work on recreational science projects just because you wanted to?

APPENDIX C

Scales from Study 1

Proactivity (Seibert et al., 1999)

1. I am constantly on the lookout for new ways to improve my life.
2. Wherever I have been, I have been a powerful force for constructive change.
3. Nothing is more exciting than seeing my ideas turn into reality.
4. If I see something I don't like, I fix it.
5. No matter what the odds, if I believe in something I will make it happen.
6. I love being a champion for my ideas, even against others' opposition.
7. I excel at identifying opportunities.
8. I am always looking for better ways to do things.
9. If I believe in an idea, no obstacle will prevent me from making it happen.
10. I can spot a good opportunity long before others can.

APPENDIX D

Revised Biodata Scale for Study 1

When you were elementary school age (11 and younger)...

Background Influences

1) Being Exposed or Encouraged for STEM

1. How often did you talk to siblings or cousins who were studying STEM in high school or college about STEM topics?
2. How often did you interact with adults in STEM fields who were not related to you?
3. What proportion of your parents, siblings, or extended family worked in a STEM career while you were growing up?
4. How often did adults in STEM careers tell you about their career?
5. How often did your parents talk to you about the importance of choosing a STEM major in college?
6. To what extent did your parents encourage you to pursue a STEM interest due to your innate talent or ability for the topic?
7. To what extent did your parents encourage you to work in a specific STEM career because that career would have plenty of jobs available?
8. To what extent did your parents encourage you to pursue STEM at the expense of your non-STEM interests?
9. How often did adults in STEM careers tell you that you would do well in a similar career?
10. How much influence did your parents have on the school topics you were interested in?

2) Being Provided STEM Resources

11. How likely were your parents to provide you with the materials to work on STEM-related projects?
12. How often did you attend multi-day STEM events, such as STEM-related summer camps?
13. How often did you attend one-day science, math, or engineering events, such as talks or demonstrations?
14. How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?
15. How often did your parents encourage you to work on STEM-related projects?
16. How often did your parents or teachers give you STEM-related books, toys, or other STEM gifts?
17. How willing were your parents to pay for new STEM activities for you to try?
18. To what extent did your family provide you with books, movies, or TV shows about a certain STEM career path?
19. Were your parents more likely to pay for you to participate STEM activities than in non-STEM activities?

20. How willing were your parents or other family members to pay for hands-on STEM project materials for you?

Learning Experiences

3) Having Hands-on STEM Experiences

21. How likely were you to get bored of working on mandatory hands-on STEM activities? (RC)
22. How much access did you have to hands-on STEM materials at home?
23. How much did you generally prefer to work on hands-on STEM activities compared to other hobbies?
24. How much did you look forward to working on hands-on STEM activities in your classes?
25. How often did you do hands-on math assignments, such as math blocks, puzzles, geometry projects, or filling in graphs or charts?
26. How often did you go on field trips to activities or places where you were able to touch or build things?
27. How often did you work on engineering, building, or construction projects in class?
28. How often did you work on science experiments or projects in class?
29. How often did you work on science fair projects at school?
30. How often did you choose to work on hands-on STEM activities (e.g. experiments, building projects, lab activities) after school when you had the choice to do other activities?

4) Participating in STEM Competitions

31. How likely were you to participate in math competitions that were voluntary?
32. How likely were you to participate in science competitions that were voluntary?
33. How likely were you to spend a lot of time after school preparing for math competitions?
34. How likely were you to spend a lot of time after school preparing for science competitions?
35. How much did you look forward to opportunities to participate in math competitions?
36. How much did you look forward to opportunities to participate in science competitions?
37. How often did you participate in math competitions?
38. How often did you participate in science competitions?
39. To what extent did your parents expect you to participate in science competitions?
40. To what extent did your teachers encourage you to participate in science competitions?

5) Receiving Help on School Assignments

41. How capable were your parents of helping you on a math assignment if you needed help?
42. How capable were your parents of helping you on a science assignment if you needed help?
43. How helpful did you think your parents would be if you had trouble with an assignment?
44. How helpful were most of your teachers if you were struggling with an assignment?

45. How often did your parents ask you if you needed help with your homework?
46. How often did your parents help you study for tests?
47. How often did your teachers specifically encourage you in particular to do well in class?
48. How skilled were most of your teachers at explaining new topics to the class?
49. To what extent did you believe your teachers prioritized helping other students over you? (RC)
50. To what extent did your parents expect you to figure out difficult class assignments on your own? (RC)

6) Proactive or Voluntary STEM Behaviors

51. How willing were you to approach your teacher with science or math questions after class?
52. How comfortable did you feel asking your teacher science or math questions during class?
53. How likely were you to ask for STEM-related gifts for your birthday or another holiday?
54. How likely were you to ask your parents for help with a class assignment if you were struggling with it?
55. How likely were you to ask your parents for parts or materials so you could work on hands-on STEM activities?
56. How likely were you to choose to attend or participate in STEM events that were voluntary?
57. How likely were you to look up instructional videos or books to complete difficult assignments on your own?
58. How likely were you to seek out information on STEM events you wanted to attend?
59. How likely were you to work on extracurricular or extra credit math assignments just because you wanted to?
60. How likely were you to work on recreational science projects just because you wanted to?

APPENDIX E

Career Outcome Expectancies Scales

1) Mathematics & Science Career Outcome Expectancies (Fouad et al., 1997)

This was originally a middle school test (Fouad et al., 1997), that I altered slightly to apply to college students (changing items to refer to career plans rather than high school plans).

Instructions: Please indicate the degree to which you agree or disagree with each statement below by selecting one of the following. (*1 = Strongly Disagree; 2 = Disagree; 3 = Uncertain; 4 = Agree; 5 = Strongly Agree*)

1. If I take a lot of college math courses, then I will be better able to achieve my future goals. (M)
2. If I learn math well, then I will be able to work in lots of different types of careers. (M)
3. If I take a math course, then I will increase my GPA. (M)
4. If I do well in science classes in college, then I will do well in my future career. (S)
5. If I get good grades in my math courses, then my parents will be pleased. (M)
6. If I do well in my science sciences, then I will be better prepared for my future career. (S)
7. I plan to take more math classes than required to graduate. (M)
8. I intend to take more science classes than the minimum required for my major. (S)
9. I am committed to studying hard in my biology, chemistry, or physics classes. (S)
10. I intend to enter a career that will use math. (M)
11. I am determined to use my science knowledge in my future career. (S)
12. I intend to enter a career that will use science. (S)

2) Career Outcome Expectations (Hazari et al., 2010)

This is a six-point Likert scale ranging from 1 (“Not at all important”) to 6 (“Very important.”) It was originally used to assess physics identity in high school students; I altered the instructions slightly to apply to college students.

Instructions: Please rate these items in terms of their importance for your career satisfaction once you graduate from college.

(Extraneous)

1. Making money
2. Having others working under your supervision
3. Having an easy job
4. Becoming well known

(Intrinsic Reward)

5. Inventing new things
6. Making use of your talents/abilities
7. Developing new knowledge and skills
8. Having an exciting job

(Personal Time)

9. Having time for yourself/friends
10. Having time for family

(People-Related)

11. Helping other people
12. Working with people rather than objects

(Other Outcome Expectations)

13. Having job security

14. Making your own decisions

15. Working in an area with lots of job opportunities

APPENDIX F

Self-Efficacy Scales

1) Math Self-Efficacy

For math self-efficacy, I adapted two items from a middle school self-efficacy questionnaire (Fouad et al., 1997), to be appropriate for college students, as well as six items from Betz and Hackett's (1983) scale.

Instructions: Indicate your ability to do each of the following statements below. (1 = Very High Ability; 2 = High Ability; 3 = Uncertain; 4 = Low Ability; 5 = Very Low Ability)

1. Earn at least a 3.5 average GPA in all math courses
2. Get an A- or higher in upper-level math classes.
3. Add two large numbers (e.g., 5739 + 62543) in your head
4. Set up a monthly budget for yourself
5. Figure out the tip on your part of a dinner bill split eight ways
6. Compute your car’s gas mileage
7. Figure out which of two summer internships is the better offer; one with a higher hourly pay but no benefits, the other with a lower hourly pay plus room, board, and travel expenses
8. Figure out how much you would save if there is a 15% markdown on an item you wish to buy

2) Science Self-Efficacy

For science self-efficacy, I adapted ten items from a questionnaire by Smist (1993) to be appropriate for college students.

Instructions: Indicate your ability to do each of the following statements below. (1 = Very High Ability; 2 = High Ability; 3 = Uncertain; 4 = Low Ability; 5 = Very Low Ability)

1. Earn an A in a first-year college biology course
2. Earn an A in a first-year college chemistry course
3. Earn an A in a first-year college physics course
4. Graduate with a 3.5 or higher GPA in your science, math, and engineering courses
5. Understand concepts in a college biology textbook
6. Use a microscope
7. Understand abstract chemical concepts
8. Use chemical formulas and equations
9. Perform lab experiments with simple machines
10. Do physics lab assignments well

3) Major self-efficacy scale (Betz & Hackett, 1981)

This scale is based on the educational requirements subscale of the college major self-efficacy scale. I included all the classic STEM majors, plus the most common majors on the National Center for Education Statistics' list of most popular majors in the US.

Instructions: Please rate your level of confidence in being able to successfully complete graduate with the following majors from 1 = "Completely Unsure" to 10 = "Completely Sure."

1. Engineering
2. Math
3. Physics
4. Chemistry
5. Biology

6. Computer Science
7. Astronomy
8. Geology
9. Statistics
10. English Literature
11. History
12. Accounting and Finance
13. Visual and Performing Arts
14. Marketing
15. Education
16. Psychology
17. Health Sciences (including pre-med)

APPENDIX G

STEM Interest Scales

1) Math Interest (Frenzel et al., 2010)

I adapted several of these items to be more specific to college-level math interest.

Responses are scored using 5-point Likert agreement scales ranging from *1 = Strongly Disagree* to *5 = Strongly Agree*.

1. I am interested in calculus
2. I am interested in advanced algebra
3. I like to read non-fiction books related to mathematics
4. Solving math problems is one of my favorite activities
5. I often find the things we deal with in mathematics really exciting
6. After a math class, I am often curious about what we are going to do in the next lesson
7. I would like to learn much more about some of the topics we deal with in mathematics classes

2) STEM Career Interest Test (Milner et al., 2014)

Instructions: Please rate how interested you would be in performing the following tasks.

Responses are scored using 5-point Likert agreement scales ranging from *1 = Strongly Disinterested* to *5 = Strongly Interested*.

1. Redesign an engine to improve fuel efficiency.
2. Measure the speed of electrons.
3. Maintain the main generator in a power plant.
4. Analyze problems in aircraft design.
5. Study the nature of quantum physics.

6. Study the laws of gravity.

7. Apply mathematical techniques to practical problems.

8. Create a computer database.

APPENDIX H

Choice Goal and Choice Action

1. What was the major you declared when you first entered college? If you did not declare a major, which major did you think you would most likely choose at the time?
2. Which major do you think you are most likely to choose now?

APPENDIX I

Revised Biodata Scale for Study 2

When you were elementary school age (11 and younger)...

Academic Background Experiences

General Parent Influence and Support

1. How capable were your parents of helping you on a math assignment if you needed help?
2. How capable were your parents of helping you on a science assignment if you needed help?
3. How helpful did you think your parents would be if you had trouble with an assignment?
4. How much access did you have to hands-on STEM materials at home?
5. How much influence did your parents have on the school topics you were interested in?
6. How often did you ask your parents for help with a class assignment if you were struggling with it?
7. How often did your parents ask you if you needed help with your homework?
8. How often did your parents help you study for tests?
9. How willing were your parents or other family members to pay for hands-on STEM project materials for you?
10. How willing were your parents to pay for new STEM activities for you to try?
11. To what extent did your parents expect you to figure out difficult class assignments on your own? (RC)
12. What proportion of your parents, siblings, or extended family worked in a STEM career while you were growing up?

Skill and Helpfulness of Teachers

13. How comfortable did you feel asking your teacher science or math questions during class?
14. How helpful were most of your teachers if you were struggling with an assignment?
15. How often were your teachers enthusiastic and encouraging in their classroom teaching style?*
16. How skilled were most of your teachers at explaining new topics to the class?
17. How willing were you to approach your teacher with science or math questions after class?
18. To what extent did your teachers provide more support to other students than to you? (RC)*

STEM Learning Experiences

Information-Oriented Receipt of STEM Knowledge

19. How often did adults in STEM careers tell you about their career?
20. How often did adults in STEM careers tell you that you would do well in a similar career?
21. How often did you attend multi-day STEM events, such as STEM-related summer camps?
22. How often did you attend one-day science, math, or engineering events, such as talks or demonstrations?
23. How often did you go on field trips to activities or places where you were able to touch or build things?
24. How often did you interact with adults in STEM fields who were not related to you?
25. To what extent did you look forward to working on hands-on STEM activities in your classes?

26. How often did you participate in non-competitive science, math, or engineering-focused events for students, such as career days, field trips, or exhibitions?
27. How often did you work on engineering, building, or construction projects in class?
28. How often did your parents or teachers give you STEM-related books, toys, or other STEM gifts?
29. How often did you talk to relatives (e.g. older cousins or siblings) who were studying STEM in college about their STEM major?*

Extracurricular Math Competitions & Activities

30. How often did you participate in math competitions?
31. How often did you participate in math competitions that were voluntary?
32. How often did you spend a lot of time after school preparing for math competitions?
33. How often did you did you look forward to opportunities to participate in math competitions?
34. How often did you work on extracurricular or extra credit math assignments just because you wanted to?
35. How likely were you to choose to work on math assignments, such as math blocks, puzzles, geometry projects, or filling in graphs or charts, when you had the choice to do other activities?*

Extracurricular Science Competitions & Activities

36. How likely were you to choose to work on science activities (such as experiments or hands-on science projects) after school when you had the choice to do other activities?*
37. How likely were you to get bored of working on extracurricular science activities during class?*
38. How much did you generally prefer to work on hands-on building or construction hobbies compared to other hobbies?*
39. How much did you look forward to participating in science competitions?*
40. How much time did you spend after school preparing for science competitions or science fairs?*
41. How often did you participate in science competitions?
42. How often did you work on science experiments or projects in class?
43. How often did you work on science fair projects at school?
44. To what extent did your parents expect you to participate in non-required science competitions?
45. To what extent did your teachers encourage you to participate in science competitions?

Proactive and Voluntary STEM-Seeking Behavior

46. How likely were you to ask an older sibling or adult how to solve a homework problem you were struggling with?*
47. How likely were you to look up on your own how to solve a homework problem you were struggling with?*
48. How often did you ask for STEM-related gifts for your birthday or another holiday?
49. How often did you ask your parents for parts or materials so you could work on hands-on STEM activities?
50. How often did you choose to attend or participate in STEM events that were voluntary?
51. How often did you seek out information on STEM events you wanted to attend?
52. How often did you work on recreational science projects just because you wanted to?
53. To what extent did your family provide you with books, movies, or TV shows about a certain STEM career path because you showed an interest in it?*

Parental Statements of Support for STEM

54. How likely were your parents to work on science or engineering projects with you?*
55. How often did your parents talk to you about the importance of choosing a STEM major in college?
56. To what extent did your parents encourage you to pursue a STEM interest due to your innate talent or ability for the topic?
57. To what extent did your parents encourage you to pursue STEM at the expense of your non-STEM interests?
58. To what extent did your parents encourage you to work in a specific STEM career because that career would have plenty of jobs available?
59. To what extent did your parents expect you to work hard on your science projects, even if it meant you had less free time?*
60. To what extent were your parents more willing to pay for you to participate STEM activities than in non-STEM activities?

*Note: *Altered items*

APPENDIX J

Other Scales Used in Study 2

Standardized Test Performance

1. What was your highest SAT score by test section? Please estimate scores on each section if you cannot remember the exact numbers.
   a. Math
   b. Reading and Writing
2. What was your highest ACT score by test section? Please estimate scores on each section if you cannot remember the exact numbers.
   a. Math
   b. Reading
   c. Science
   d. Writing

Major Choices

1. What was the major you declared when you first entered Rice? (If you did not declare a major, which major did you think you would most likely choose at the time?)
2. What was your second choice major when you first entered Rice?
3. Which major do you think you are most likely to graduate with now?
4. How confident are you that you will graduate with this major?
5. If you do not end up graduating with your most likely major, what is the second most likely major that you will graduate with?

All currently available Rice majors listed.

Perceptions of First Semester Performance

1. Which of the following reflects how you feel about the quality of your effort in your classes last semester? (Very Little Effort (1) to The Maximum Amount of Effort (5))
2. Which of the following reflects how you feel about your course grades last semester? (Very Unsatisfied (1) to Very Satisfied (5))

Career Plans

1. When you started Rice, which career field(s) did you think you were most likely to enter when you graduated (and after any required post-undergraduate education)? You may select up to three.
2. Which career field(s) do you currently think you are most likely to enter when you graduate (and after any required post-undergraduate education)? You may select up to three.

Industry Options (select up to three).

- Agriculture, Food & Natural Resources
- Architecture & Construction
- Arts, Audio/Video Technology & Communications
- Business Management & Administration
- Education & Training
- Engineering[a]
- Finance
- Government & Public Administration
- Health Science Practitioner (e.g. physician, dentist)
- Hospitality & Tourism
- Human Services
- Information Technology & Computer Science[b]
- Law, Public Safety, Corrections & Security
- Manufacturing
- Marketing
- Research (e.g. at university or private firm)
- Science or Math[a]
- Transportation, Distribution & Logistics

[a]The "Science or Math" item was separated from the "Engineering" item; [b]"Computer Science" was added to the "Information Technology" item to explicitly capture this career path