ABSTRACT

Title of Dissertation: BUILDING READINESS AND INTENTION
TOWARDS STEM FIELDS OF STUDY AMONG
HIGH SCHOOL STUDENTS

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This dissertation study investigated the cognitive and contextual influences

contributing to the developmental process that high school students undergo in preparing

for and considering the selection of an academic major in a STEM field. Guided by the

theoretical framework of SCCT (Lent et al., 1994) and Wang's (2013) conceptual model,

I developed a new conceptual model for understanding the STEM readiness and intention

development process. The STEM Readiness and Intention Development (SRID)

Conceptual Model addresses gaps in previous research, such as the absence of parental

involvement. In addition, my research design overcame measurement and analytic

shortcomings, while examining the moderating effect of self-efficacy on high school

students' intention to major in a STEM field.

Through the use of structural equation modeling with data from the High School

Longitudinal Study of 2009, I tested the SRID Conceptual Model and examined the

indirect effects of self-efficacy on high school students' intention to major in a STEM

field. The results of these analyses suggest several cognitive and contextual influences

contributing to building STEM readiness and students' intention to major in STEM during high school. This study revealed that STEM readiness is impacted directly by several factors, including SES, math ability, parental involvement, math self-efficacy, science self-efficacy, math interest, and science interest. Intention to major in STEM is directly impacted by STEM readiness, as well as high school students' interest in math and interest in science. In addition, I found that self-efficacy in math and science had a mediating effect through math and science interest on high school students' intention to major in STEM, emphasizing the critical impact of self-efficacy throughout the career development process.

Overall, this dissertation study expands our knowledge of the process that leads high school students to become prepared for and aspire to pursue majors in STEM. Through facilitating this process among all student populations, we may improve overall enrollment and persistence through the STEM pipeline and contribute to the national goal of increasing the number of graduates in STEM fields of study.

BUILDING READINESS AND INTENTION TOWARDS
STEM FIELDS OF STUDY AMONG HIGH SCHOOL STUDENTS

by

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Chapter I: Introduction

Background of the Problem

National growth in the fields of science, technology, engineering, and mathematics (STEM) impacts the global competitiveness and economic development of the United States (National Science Board, 2015; 2016). Historically, increases in STEM workforce have enabled economic growth, job increases, and the development of new industries and technologies (Langdon, McKittrick, Beede, Khan, & Doms, 2012). With the rapid development of a technology-driven world, there is an increased importance of knowledge in STEM fields for the current generation and future generations. According to the President's Council of Advisors on Science and Technology (PCAST) (2012) STEM knowledge is beneficial to the lives of all Americans, as achieving STEM-literacy in our nation advances innovation, economic growth, and global competitiveness. The U.S. Bureau of Labor Statistics (BLS) predicts that by 2022, occupations in STEM fields will be expected to grow to more than 9 million (Vilorio, 2014).

Despite this national need for growth in STEM fields, the United States only grants approximately 400,000 bachelor degrees in STEM fields each year, which accounts for less than a quarter of all degrees awarded (National Center for Education Statistics, 2015). In comparison to other nations, the United States produces only 9% of all degrees in science and engineering, falling behind India (23%), China (23%), and the European Union (11.5%) (National Science Board, 2016). Among industrialized nations, the United States is ranked 29th in mathematics and 22nd in science. To address global competitiveness in STEM, the Obama Administration made a strong commitment to prioritize STEM education over the past decade, calling for a national goal of producing

one million additional college graduates with degrees in STEM fields and becoming a leader in math and science. The Presidential report from PCAST (2012), which focuses on strategies to meet these goals indicates that the United States must increase the recruitment and retention of STEM majors to achieve the goal of producing one million STEM graduates.

Policymakers and legislators at both the federal and state level have also called for national efforts to improve upon student pathways in STEM, particularly from high school (National Science Board, 2016). In alignment with the Common Core State Standards, K-12 reform efforts have focused on increasing course-taking in math and science, while improving on student learning in math and science, among other career and college readiness standards (National Science Board, 2016). Continued efforts are likely to be implemented throughout the STEM pipeline, particularly at the high school level when students are learning fundamental knowledge in math and science, and facing the decision of whether to consider pursuing postsecondary education in a STEM field (Ginzberg, 1972; Ireh, 1999). In order to improve upon STEM enrollment and implement effective and targeted intervention strategies, it is critical to have a foundational understanding of the process that high school students undergo in becoming ready for and considering a major in a STEM field of study in postsecondary education.

Given the importance of increasing the number of STEM graduates in our nation (National Science Board, 2015), decades of previous research focused on student persistence and degree completion in STEM fields of study (Cole & Espinoza, 2008; Crisp, Nora, & Taggart, 2009; Graham, Frederick, Byars-Winston, Hunter, & Handelsman, 2013; Palmer, Maramba, & Dancy, 2011; Watkins & Mazur, 2013).

However, much of this research has not addressed the experiences of high school students in the process of preparing for and intending to major in a STEM field, nor the various influences impacting this process through time. The research that has emerged in this area is limited in its data, measurements, and analytical approach, limiting the extent to which this research can provide us with a clear understanding of the STEM readiness and intention process unfolding through time (Chen & Weko, 2009; Crisp et al., 2009; Moakler & Kim, 2014; Sax, Kanny, Jacobs, Whang, Weintraub, & Hroch, 2016; Wang, 2013a). To address the national priority of increasing the recruitment and retention of students into STEM majors, there is a need to focus research and practice into facilitating efforts much earlier in the STEM education pipeline to high school. High school is a particularly critical time period when students are faced with the initial decision of continuing their education to postsecondary education and declaring their major field of study.

High School Context

While career interests develop throughout the lifespan, high school is an important time period in which occupational aspirations and interests begin forming in alignment with goals, behaviors, and actions (Ginzberg, 1972; Holland, 1997; Paa & McWhirter, 2000; Pajares & Urdan, 2006). During high school, adolescents begin the process of self-exploration, and begin to become aware of how their interests and values contribute to their occupational expectations and possible career choices (e.g., Bandura, 2006; Paa & McWhirter, 2000; Pajares, 2005).

Furthermore, it is during these critical high school years that students take foundational educational courses in math and science, which prove critical when pursuing

STEM majors in postsecondary education (Berkner & Chavez, 1997; Chen, 2013). More specifically, high school is the time when students more actively begin applying their mathematical abilities in the classroom setting (Eccles & Midgley, 1990; Mattern, Radunzel, & Westrick, 2015). This application of and use of mathematical abilities during adolescence contributes to the development of self-efficacy (Bandura, 2006; Green, Miller, Crowson, Duke, & Akey, 2004; Pajares, 2005; Pajares & Urdan, 2006). Moreover, the cognitive experiences and courses taken during high school contribute to further development of career interests (Lent, Brown, & Hackett, 1994; Sadler, Sonnert, Hazari, & Tai, 2012; Seymour & Hewitt, 1997). In addition to the cognitive and social development during high school, there are key external and contextual factors that contribute to the development process in building readiness and intention toward STEM majors. These include influential factors such as socioeconomic status and parental involvement (Cabrera & LaNasa, 2000; Fan & Chen, 2001; Keller & Whiston, 2008; Paa & McWhirter, 2000). Ultimately, learning experiences and social/cognitive development in high school, in addition to the interaction of background and environmental factors, contribute to the developmental process that high school students undergo in preparing for and intending to major in a particular field.

As suggested in previous research, intention to major in STEM is regarded as an important factor related to both entrance into and success in STEM fields of study (Mattern et al., 2015; National Science, Foundation, 2014; Wang, 2013a). According to Mattern and colleagues (2015), a student's intention to major in a STEM field as a high school student as well as their measured interest in STEM contributed to the prediction of success in STEM major degree completion. Furthermore, intention to major in STEM has

been recognized as the strongest predictor of actual enrollment into STEM fields of study (Wang, 2013a). Building on this body of research, this dissertation study focuses on understanding the processes and factors contributing to the preparation for a STEM major and the intention to major in a STEM field of study among high school students.

Statement of the Problem

Despite the importance of understanding the process high school students undergo in preparing for and considering the selection of a STEM major, little is known about the factors influencing this process through time. In order to address the national agenda of producing one million additional STEM graduates, research must shift focus to recruiting and preparing students for STEM fields of study during high school. Before intervention and recruitment practices can be implemented, it is critical to first develop a better understanding of the factors impacting the process that high school students undergo in preparing for and deciding to major in a STEM field. The problem this study addresses is the limited understanding of and knowledge about the process for high school students in preparing for a major in STEM, and the factors influencing students' consideration of a STEM major in postsecondary education.

Purpose of the Study

The purpose of this study was to investigate the various cognitive and contextual influences contributing to the developmental process that high school students undergo in preparing for and considering selection of an academic major in a STEM field. The study sought to address gaps in previous research, such as analytic and measurement shortcomings, to provide a better understanding of the STEM readiness and intention

development process throughout students' high school experience. In addition, this study sought to measure the impact of self-efficacy on students' intention to major in a STEM field. As such, this study was guided by the following research question and sub research question:

- What are the cognitive and contextual factors impacting the developmental process high school students undergo in building readiness and intention toward a major in STEM fields of study?

    - What is the indirect effect of STEM self-efficacy on the intention to major in a STEM field?

Overview of the Proposed Conceptual Model

In order to address these research questions, I proposed a new conceptual model for understanding the developmental process high school students undergo in building readiness and intention toward a STEM field of study. My proposed model was guided by the theoretical framework of Social Cognitive Career Theory (SCCT) (Lent et al., 1994). It also integrated college readiness components of Wang's (2013) conceptual model of STEM choice, while addressing gaps - such as the absence of parental involvement - and overcoming measurement and analytic shortcomings in extant research.

Summary of Theoretical Foundations

My dissertation study was primarily guided by the model of SCCT (Lent et al., 1994). SCCT is based on Bandura's social cognitive theory (1986, 2001, 2002, 2005) and postulates that the career development process is influenced by social and cognitive

factors and contextual influences. The SCCT model, described in more detail in Chapter 2, reflects the complex relationships and interactions among cognitive concepts (self-efficacy, outcome expectations, interests, and goals) with contextual factors (including background contextual affordances, personal inputs, and contextual influences proximal to choice behavior). These concepts directly or indirectly affect each other and continue to do so throughout the developmental process.

The model of SCCT has been a foundational framework guiding studies on career interest development and career choice, throughout the academic pipeline (Lent et al., 2003; 2008). Most studies applying SCCT have applied the model to samples of college students already pursuing degrees in STEM fields of study (Moakler & Kim, 2014; Sax et al., 2015). However, prominent research conducted by Wang (2013a; 2013b) *does* focus on examining the STEM major choice process for high school students through postsecondary education. Also guided by SCCT, Wang's research sought to understand the STEM major choice process and develop a conceptual model for understanding the selection of a STEM major among high school students. Furthermore, Wang's model links self-efficacy, learning experiences, interests and goals, while also including a construct for college readiness.

Wang's (2013a) study was one of the first studies to use nationally-representative longitudinal data to examine the STEM choice process for high school students. Moreover, her work emphasizes the complexity of the process leading to students' entrance into a STEM field of study. Wang recommends the use of longitudinal data in application of SCCT and the use of structural equation modeling as the statistical analytic approach in understanding the STEM choice process (Wang, 2013a; 2013b). Her work

calls attention to the continued need for investigation of the process for high school students in the STEM pipeline.

Summary of the SRID Conceptual Model

To address my research questions I proposed a new conceptual model for understanding the STEM readiness and intention developmental process. This model builds upon SCCT and components of Wang's (2013) model of STEM choice, incorporating important constructs and measurements omitted by the extant literature (including parental involvement). My proposed model, called the *STEM Readiness and Intention Development (SRID) Conceptual Model*, is displayed in Figure 1. While conceptually framed by SCCT, it also integrates many components of Wang's (2013a) conceptual model of STEM choice.

The SRID Conceptual Model illustrates the various factors, both cognitive and contextual, influencing high school students' development in relation to preparing for and intending to major in a STEM field. Aligned with SCCT and previous research, my model includes self-efficacy and interest in STEM-related content as key cognitive components in the developmental process (Bandura, 1994; Hackett & Betz, 1995; Lent et al., 2003; Rittmayer & Beier, 2008). Guided by Wang's inclusion of college readiness in her conceptual model, my proposed model incorporated a STEM-specific construct of readiness, termed *STEM readiness*. STEM readiness is also an operationalization of SCCT's construct of *learning experiences*, as it included high school students' exposure to and performance in STEM-related coursework (Chen, 2013; Ferry et al., 2000; Mattern et al., 2015; Sadler et al., 2012). I regard the main outcome variable in the SRID Conceptual Model, *intention to major in STEM*, as a cognitive component aligned with

SCCT. Wang's (2013) model also includes the intention to major in STEM as a key factor in the STEM choice process, with her findings suggesting that intention to major has the most significant influence on actual entrance into STEM fields. As such, my model includes *intention to major* as the main outcome variable.

The SRID Conceptual Model represents background characteristics through socioeconomic status (SES) (*background contextual affordance*) and mathematics ability (*personal input characteristics*). Including these background characteristics in the SRID model reflected the role that SES (Cabrera & LaNasa, 2000; Eagle, 1989; Lee & Burkam, 2002; Ma, 2009; Perna, 2006) and math ability (Cabrera & LaNasa, 2000; Conley, 2007; Hackett, 1985; Rohde & Thompson, 2007) play in the STEM readiness and intention development process. In addition, as an interpretation of SCCT's *contextual influence proximal to choice behavior*, I added parental involvement as key factor influencing the preparation for and intention to major in a STEM field. Previous research supported the inclusion of parental involvement as a key factor in the STEM readiness and intention development process (Cabrera & LaNasa, 2001; Fan & Chen, 2001; Ferry et al., 2000; Hall et al., 2001; Hill & Tyson, 2009; Jeynes, 2007).

With regard to the development of the SRID Conceptual Model, Chapter 2 provides a more detailed explanation of each component of the model and the reasoning and support for its inclusion. Chapter 2 also provides a concise review of the relevant literature pertaining to each of the components of the model, and describes the ways in which these factors are related and interconnected within the developmental process. In Chapter 3, I discuss the selected measures for each construct in the model and describe the method I used to test the SRID model with national longitudinal data. In Chapter 4, I

describe the results from the study, and the ways in which the SRID Conceptual Model was revised in light of the results.
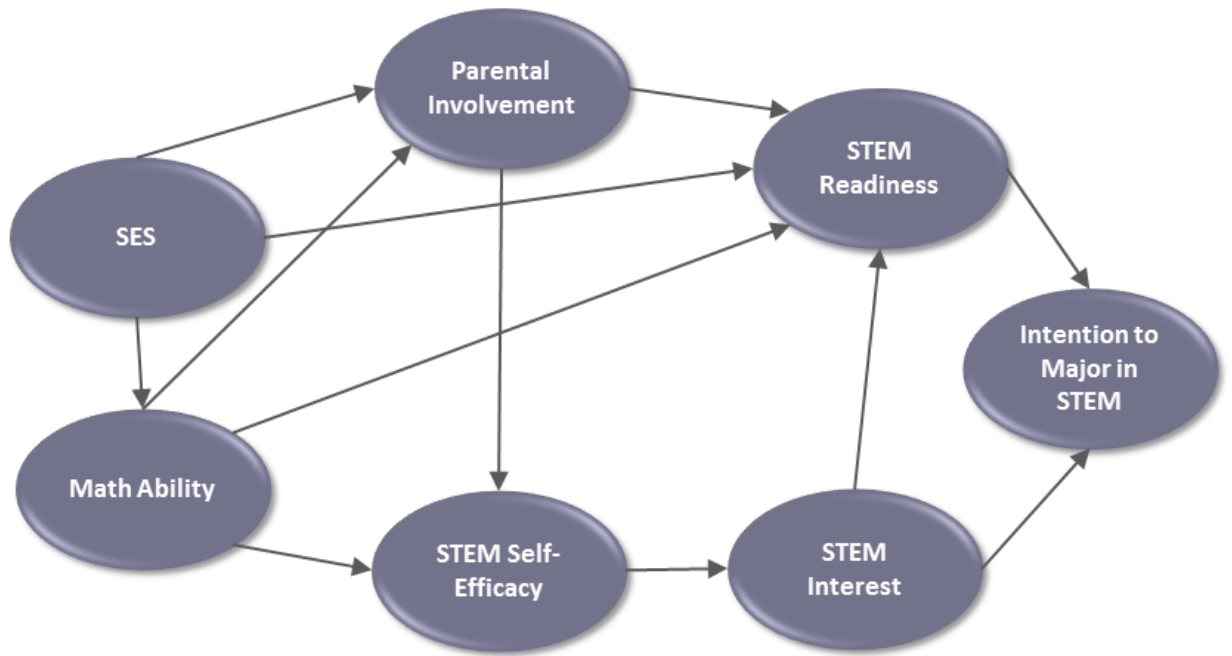
Figure 1: The STEM Readiness and Intention Development Conceptual Model

Study Significance

Summary of Research Contributions

This dissertation study contributes to the body of research on STEM pathways by examining the process high school students undergo in becoming prepared for and intending to pursue a STEM major in college. Compared to the depth of research on STEM retention and degree completion in postsecondary education (Cole & Espinoza, 2008; Crisp et al., 2009; Graham et al., 2013; Palmer et al., 2011; Watkins & Mazur, 2013), research related to the STEM readiness and intention development process for high school students is a newer and less explored area of research. Scholars working on

relevant research are beginning to investigate student major choice selection, the contextual impacts on the career decision-making process, and our understanding of pathways into STEM majors (Chen, 2013; Committee on STEM, 2013; Crisp, Nora, & Taggart, 2009; Lent et al., 1994; 2000; 2001; 2003; Ma, 2009; Wang, 2013b). However, much of this research has not documented the process students undergo in preparing for and intending to major in STEM during high school. The relevant research that has been conducted in this topic area is limited in its analytic approach, data, and measurements[1].

This study addressed the analytic approach limitations through conducting structural equation model (SEM) on a nationally-representative sample of high school students from a longitudinal database. Furthermore, this study improved upon the measurement components of previous work, appraising key constructs with STEM-specific measures in the academic domains of math and science. In addition, given the importance of parental involvement and support in students' future decision-making and preparation during adolescence (Cabrera & LaNasa, 20000; Fan & Chen, 2001; Ferry, Fouad, & Smith, 2000; Jeynes, 2007; Keller & Whiston, 2000), the SRID Conceptual Model included parental involvement as a key factor influencing the STEM readiness and intention development process for high school students.

Summary of Implications

The development and testing of the SRID Conceptual Model contributes to improving on our knowledge of STEM readiness and intention development among students during high school. This study and model can provide policymakers and

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[1] Critiques and limitations of prior research are addressed in detail in Chapter 2. Following this review, Chapter 3 highlights the methodological strategies I followed to address gaps in previous research, highlighting the improved analytic approach and improved data and measurements.

practitioners with a deeper and more nuanced understanding of the complexity of the

STEM readiness and intention development process. The SRID Conceptual Model

highlights the key influences impacting this process during high school, when students

are making important decisions about and academically preparing for their future field of

study. Understanding the importance of STEM readiness and intention development in

the high school context may encourage further investment of resources, among

policymakers and practitioners, dedicated to targeting interventions at the high school

level. Such strategic interventions may improve recruitment into STEM fields and

strengthen STEM pathways.

Policy. Current federal policies implemented at the K-12 and postsecondary

education levels follow the national prioritization of STEM education. For example, the

Every Student Succeeds Act, which replaced "No Child Left Behind," has a potential

funding stream specifically geared toward STEM activities and programming in school

and afterschool programs (Afterschool Alliance, n.d.; U.S. Department of Education,

n.d.). In addition, some practices at the K-12 level have been integrated within the

Common Core State Standards, while other programs have adopted STEM focuses to

improve the strengthening of math and science skills through K-12 education (Lee,

Quinn, & Valdes, 2013; National Science Board, 2016). Moreover, given the national

focus on producing STEM graduates, policymakers have invested significant resources at

the postsecondary educational level, to improve STEM retention and facilitate the

persistence of students in STEM fields of study (Chen, 2013; Committee on STEM,

2013; PCAST, 2012).

However, despite the implementation of current policies and practices, our nation

must produce an additional one million graduates in STEM fields (PCAST, 2012). To achieve this goal, there must be targeted and strategic implementation of policies and intervention programs, guided by and based upon empirical evidence and research (PCAST, 2012). The implementation and interventions require a robust foundation of knowledge about the experiences of high school students navigating the STEM readiness and intention development process, as well as the various influences impacting this process. Such a foundational knowledge base can allow for the development of policies specifically targeting factors that directly or indirectly impact students throughout high school. For example, based on the findings of this study, policymakers could propose and support policies and programs that encourage and prepare parents (and other family members) to be involved with their students in discussions about college and plans for the future. In addition, programs that focus on developing self-efficacy and interest in math and science may contribute to a greater likelihood of students' becoming prepared for and intending to major in a STEM field of study.

   Practice. At the practical level, the SRID Conceptual Model may guide teachers, counselors, and administrators in implementing best practices for facilitating high school students' navigation of the STEM readiness and intention development process. Understanding of the conceptual model can encourage practitioners to acknowledge the interconnected influences contributing to movement through the STEM pipeline and identify the ways in which these pathways can be strengthened for individual and groups of high school students. For example, the SRID model draws attention to the influences that parental involvement, STEM self-efficacy, and STEM interest play in STEM readiness and the intention to major in STEM. Given the significant role of parental

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involvement in this process, practitioners could consider intervention in programs and practices at the high school level that strategically involve parents or family members. Acknowledging the impact of STEM self-efficacy and STEM interest on building STEM readiness and intention to major in STEM, practitioners could also focus on designing and implementing intervention programs that encourage the development of self-efficacy in math and science domains and cultivate interest and enjoyment in math and science. In the classroom or school context, teachers and counselors may focus on implementing strategies to develop self-efficacy and interest in math and science among students. This may include positive reinforcement, open-ended questioning and discussions, and increasing availability outside of the classroom (Haskell, 2016). Research strongly suggests that interactive and meaningful experiences outside of the classroom can develop self-efficacy in STEM (Bandura, 1994; Carpi, Ronan, Falconer, & Lents, 2007; Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; Rittmayer & Beier, 2008).

Chapter Summary

This chapter provided an introduction to my dissertation study on the developmental process high school students undergo in building readiness and intention toward a STEM field of study. After providing a background and context of the problem, I stated the problem to be addressed and the purpose of this study. In addition to identifying the key influences on STEM readiness and intention development for high school students, this study sought to develop and test a conceptual model interpreting this process. In briefly introducing this conceptual model, I provided a summary of the theoretical framework that guided this study, as well as an overview of the SRID

Conceptual Model. The testing of the SRID Conceptual Model contributes to the understanding of the process high school students undergo in becoming prepared for and considering the selection of a STEM major. This model highlights the important factors impacting the developmental process and the ways in which these factors influence one another throughout the high school experience. This chapter concluded with an overview of the study's significance, touching upon its contribution to the body of literature, as well as a brief summary of implications for policy and practice.

In Chapter 2, I provide a more detailed explanation of the development and components of the SRID Conceptual Model, while reviewing relevant research supporting the inclusion of each component within the model. The following chapter, Chapter 3, I explain the methodological approach to testing this conceptual model using national longitudinal data. Chapter 3 will provide an explanation for the selected measures used for each construct in the measurement and model testing. Chapter 4 will provide a detailed description of the results from testing the SRID Conceptual Model, as well as how this model evolved based on preliminary analyses. Finally, Chapter 5 will conclude with a discussion of the results in the context of the literature, and will offer implications, limitations, and directions for future research.

Chapter II: Literature Review

Introduction

The purpose of this study was to investigate the various cognitive and contextual influences contributing to the development process that high school students undergo in preparing for and considering selection of an academic major in a STEM field. The study addressed gaps in previous research to provide a better understanding of this developmental process throughout students' high school experience. In addition, this study measured the impact that STEM self-efficacy has on students' intention to major in a STEM field. As such, this study was guided by the following research question and sub research question:

- What are the cognitive and contextual factors impacting the developmental process high school students undergo in building readiness and intention toward a major in STEM fields of study?

  - What is the indirect effect of STEM self-efficacy on the intention to major in a STEM field?

This literature review summarizes foundational research in the areas of STEM-field preparation related to these research questions. The selection of literature highlights what is known and unknown in this area of research, focusing on entrance into STEM fields and the decision to major in STEM. This chapter begins by introducing the theoretical framework guiding this dissertation study. This framework has been foundational for many relevant studies seeking to explain the selection of a college major. As such, the tenets of the theory are important to address and explain prior to the review of extant literature relevant in the career decision-making process.

After introducing and describing the theoretical framework, I will review relevant research on STEM readiness and intention development, including key literature from the fields of career development and college choice. In particular, I will focus on (1) research that has applied Social Cognitive Career Theory to study career decision-making, (2) research that has identified important factors in STEM choice, and will highlight (3) the seminal work by Wang's (2013) study, which examined the STEM major choice process through high school and postsecondary education. Following this review, I will identify significant gaps and methodological limitations that currently exist in this topic of research. Upon doing so, I will discuss ways in which my dissertation study addresses these gaps and provides the opportunity for additional growth of new knowledge in this field.

After identifying what is known and unknown in existing research on STEM readiness and intention development, I will introduce my proposed conceptual model. I developed this conceptual model as an improved model for understanding the developmental process high school students undergo in building readiness and intention toward a STEM field of study. Next, I provide a review of literature on each factor included in the model and provide evidence from previous research supporting the reason for including this factor in the model, and the ways in which these factors are related to one another and to the intention to major in a STEM field. These factors include socioeconomic status (SES), math ability, parental involvement, STEM self-efficacy, STEM interest, STEM readiness, and the main outcome factor of intention to major in STEM. This chapter will conclude with an overview summary of the chapter, highlighting key points addressed throughout this literature review.

Theoretical Framework: Social Cognitive Career Theory

This dissertation study was framed and guided by the theoretical framework of Social Cognitive Career Theory (SCCT) (Lent et al., 1994). Lent, Brown, and Hackett (1994) developed the SCCT model (see Figure 2) to understand career development and the social and cognitive factors and contextual influences impacting this process. This theory has been a foundational framework guiding studies on career interest development and career choice, throughout the academic pipeline. SCCT was selected for this dissertation study as it specifically examines career development as a process students undergo in the development of interests, goals, and actions in relation to the selection of a career. In general, SCCT emphasizes the interaction of cognitive conceptions of self-efficacy, outcome expectations, and goal selection, along with the impact of contextual influences of barriers and support (Lent et al., 1994; Sharf, 2013). These concepts directly or indirectly affect each other (as displayed by the arrows in the figure) and continue to do so throughout the lifespan. For example, SCCT posits that a person's self-efficacy (such as confidence in mathematics) impacts their career interests (such as a STEM-related career), which ultimately impacts the goals a person forms and the actions/behaviors associated with those goals and interests. Overall, the SCCT model reflects the relationships and interactions among cognitive concepts (self-efficacy, outcome expectations, and goals) with contextual factors. SCCT emphasizes the interaction within and among the cognitive concepts and the impact of the personal inputs and contextual influences (Sharf, 2013).

Cognitive Components

SCCT is based on Bandura's social cognitive theory (1986, 2001, 2002, 2005),

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focusing on the interactions between the environment, personal factors (including

memories, beliefs, preferences, and self-perceptions), and actual behavior. One of the key

components of social cognitive theory and SCCT is the concept of self-efficacy. Self-

efficacy is defined as one's belief in his or her ability to succeed in specific situations or

in accomplishing a task (Bandura, 1977). SCCT suggests that self-efficacy impacts how

individuals view their own abilities and capabilities, which ultimately affect academic

performance and career development/ decision-making. Lent and his associates (1994)

suggest that self-efficacy can be a changing set of beliefs about oneself, dependent on the

context and the situation, such as the nature of the tasks, one's social and environmental

surroundings, and one's feelings of competence on similar tasks (Sharf, 2013).

Other cognitive components of the SCCT theory include outcome expectations,

interests, and goals. Outcome expectations can be defined as one's estimate or

expectations about the probability of an outcome resulting from one's engagement in a

particular behavior (Lent et al., 1994). In addition, self-efficacy and outcome

expectations contribute to the development and realization of goals. In general, SCCT

emphasizes that goals guide and organize individual's behaviors and actions. Lent and

colleagues (2003; 2008) also suggest that interests strongly mediate the impact of self-

efficacy on other cognitive components of the process, including goals and actions.

Contextual Components

SCCT argues that a person's career interests, goals, and actions can be affected by

both *background contextual factors* and *contextual influences proximal to choice*

behavior (see Figure 2*)*. Background contextual factors include one's interaction with

their own culture and gender role expectations, and the ways in which their self-concept

and learning experiences have been impacted through socialization (Lent et al., 1994). SCCT also recognizes personal inputs, such as predispositions, SES, gender, race/ethnicity, and disability/health status, as significant factors influencing this developmental process. For example, a student's natural abilities in mathematics may predispose him or her to engage more positively in learning experiences relevant to the use of mathematics skills.

According to Lent and associates, contextual influences proximal to choice behavior consist of environmental factors that are directly related to career choice concerns, such as career network contacts, role models, or external barriers (Lent et al., 2003). These proximal environmental factors moderate the relation of interests to choice goals, as well as the relation of goals to actions. For example, Lent and colleagues (2003) suggest that influential role models or familial involvement and acculturation may directly influence individual's own career choices, perhaps more strongly than personal career interests. Overall, various contextual factors (background or proximal) can either support students in their career development process or become a barrier. Supports and barriers can directly impact self-efficacy, which ultimately impact interests, goals, and actions.
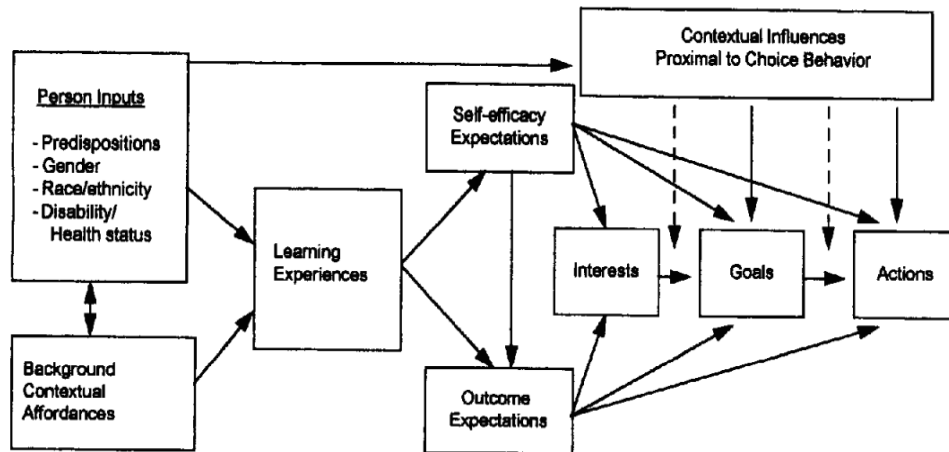
Figure 2: Social Cognitive Career Theory Model

Since the conception of the SCCT model, Lent and colleagues (1996; 2000; 2003; 2008a; 2008b; 2013) have developed several iterations of the model to reflect the growing body of understanding and developing research on what is known about the career development process, as well as the adaptation of this framework in various fields. To examine the selection of a STEM-related field of study, previous research (Moakler & Kim 2014; Sax et al., 2015; Wang, 2013a; 2013b), as well as those led by Lent and colleagues (2003; 2008a; 2008b; 2013), have relied on SCCT to guide and develop the conceptual understanding of this complex process. The next section of this literature review will identify and review the relevant and key studies on the preparation for and selection of a STEM major, many of which were also guided by this foundational work.

Literature on STEM Readiness and Intention

The national priority to increase the recruitment and retention of students into STEM majors calls attention on the need to examine the STEM readiness and intention

development process much earlier in the STEM education pipeline, to critical points in high school when students are faced with the initial decision of continuing their education to postsecondary education and declaring their major field of study (National Science Board, 2015). In order to illustrate what is known and unknown about the process for high school students, this literature review identifies and reviews research that has addressed the selection of STEM majors and important factors in STEM choice. In general, this existing body of research contributes to our growing understanding of high school students' entrance into STEM fields and supports the need for the development of my proposed conceptual model.

Applying SCCT to STEM Major Choice

SCCT has been a foundational framework in investigating the predictors of career choice behaviors, planning, and exploration. In 2003, Lent, Brown, Schmidt, Brenner, Lyons, and Treistman applied SCCT to examine choice behavior among students majoring in engineering. They relied on survey data completed by 328 students enrolled in an engineering design course in a large 4-year institution. The SCCT model was tested using correlations and path analysis, which confirmed several important relationships. In particular, this study revealed that the variables for the environmental factors of barriers and supports produced significant paths directly to self-efficacy and indirectly to goals. Aligned with SCCT, self-efficacy was predictive of both outcome expectations and interests. Self-efficacy also produced a significant indirect path to goals through interests, with interest serving as a mediator of self-efficacy and goals (Lent et al., 2003). Furthermore, background supports and barriers (such as social supports) related to choice goals and persistence indirectly through their relation to self-efficacy. While the study

highlighted the application of SCCT in the context of a STEM career, it also drew

attention to the need for future research in this area. In particular, though this study used

cross-sectional data Lent et al. (2003) suggest the use of longitudinal data to confirm the

"causal ordering of SCCT's central variables" (p. 463). They also acknowledge the need

for a larger and more appropriate (and diverse) sample of students who are in earlier

stages of the choice making process. In addition, the study calls for further research on

the application of SCCT, to clarify the paths and relationships between and among

various barriers and supports, self-efficacy, interests, and goals.

Focusing on another student population in a different STEM field, Lent, Lopez,

Lopez, & Sheu (2008) applied the model of SCCT on the choice goals in the computing

disciplines. Using a more diverse sample of students by including students from 21

predominantly White institutions (PWIs) and 21 historically Black colleges and

universities (HBCUs), Lent et al. (2008) tested a structural model of SCCT to predict

academic interests and choice goals. While more diverse in race and gender this sample

consisted of college students in their first, second, third, and fourth year (and beyond) of

postsecondary education. The analysis determined that the SCCT model accounted for

40% of the variance in interests and 33% of persistence goals of students majoring in

computing disciplines. The findings were also consistent with previous work (Lent et al.,

2003) in supporting the indirect relationship between contextual influences with interests

and goals, mediated through self-efficacy. In summary of the study's limitations, the

authors acknowledge the need for further testing with longitudinal data. The authors note

that longitudinal data would be better suited in testing the causal hypotheses of SCCT and

could support the application of the theory into practice (Lent et al., 2008).

A similar study conducted by Lent, Sheu, Singley, Schmidt, Schmidt, and Gloster (2008b) tested a longitudinal model using data from survey administered at two points in time (with a 5-month lag). The sample consisted of 209 first-year and second-year students from an introductory engineering course at PWIs and HBCUs. The study focused on exploring four core cognitive variables in the SCCT model, including self-efficacy, outcome expectations, interests, and goals. While the findings were consistent with SCCT in identifying the significant path of self-efficacy on other cognitive factors such as outcome expectations, interests, and goals, the findings interestingly did not find significance in the role of outcome expectations in the fostering of interests or goals (Lent et al., 2008b). In addition, this study's findings supported a unidirectional flow from self-efficacy to interest in comparison to a bidirectional relationship between these two variables. While this study employed a semi-longitudinal approach to examining and testing SCCT, the authors note the important need for longitudinal data in examining the process of SCCT.

The model of SCCT has also been tested among a population of female high school students who attended a science, math, and engineering career conference. Conducted by Nauta and Epperson (2003), this study utilized 4-year longitudinal data to predict high school students' decision to declare a major in science, math, or engineering. Regression analysis revealed relationships between students' college outcome expectations in science, math, or engineering, as well as their plans to become leaders in their fields of interest (Nauta & Epperson, 2003). Structural equation modeling (SEM) was also implemented to test the applied model of SCCT for the sample of high school students. The results of this modeling technique suggest a positive and significant

relationship between math-science ability and self-efficacy, as well as a significant and positive relationship between self-efficacy and science interests, supporting these key components of the SCCT framework. In contrast to SCCT, however, this analysis did not reveal a path between self-efficacy and enrolling in high school math and science courses.

Rogers and Creed (2011) also tested the model of SCCT, through the use of cross-sectional and longitudinal data of Australian high school students from grades 10 through 12. Using hierarchical regression analyses, the authors found strong support for self-efficacy and goal measures in predicting career planning and exploration among high school students between grade 10 and grade 11. While this study did not specifically examine STEM readiness or intention development, it draws attention to the complexity of career development during high school and the various interactions influencing adolescents' decisions through the career choice process.

Identifying Important Factors in STEM Major Choice

Aside from research applying SCCT to the selection of a STEM major, some research has sought to identify the key characteristics of high school students enrolling in STEM majors. This line of research has also emphasized the role of background and environmental factors in shaping the choice of major (Chen & Weko, 2009; Crisp, Nora, & Taggart, 2009; Moakler & Kim, 2014; Sax et al., 2016).

Crisp, Nora, and Taggart (2009) conducted a study seeking to identify student characteristics and factors that could predict whether or not a student from a Hispanic Serving Institution (HSI) decided to major in STEM. The study sought to identify pre-college, environmental, and student characteristic predictors of whether or not the college

student majored in a STEM field. Through the use of logistic regression analyses, the study results indicated that the decision to declare a major in STEM was influenced by gender, ethnicity, SAT math score, and high school grades (Crisp et al., 2009). Though the study is limited to students at Hispanic Serving Institutions, the findings from this study contribute to the understanding about the various factors that influence students' decision to pursue a degree in a STEM field. This research importantly notes the significance of demographic factors and pre-college experiences, such as college preparation, academic experiences in math and science, and math achievement in the decision to enroll in a STEM major (Crisp et al., 2009).

Moakler and Kim's (2014) research also investigated influences relevant to STEM major choice, among first-time, full-time freshmen attending 617 4-year postsecondary institutions in 2003. Guided by SCCT (Lent et al., 1994) and using cross-sectional data from the Cooperative Institutional Research Program (CIRP), Moakler and Kim's main research question focused on how background factors, such as gender, race, SES, and academic preparation affect STEM major choice. As theorized by SCCT, Moakler and Kim also examined the impact of self-efficacy through including both academic and math-specific confidence as a predictor of the choice of major among the college freshmen. Logistic regression revealed several positive indicators of STEM major choice, including "having parents with a STEM occupation, having higher SAT scores, having higher high school GPA, having spent more hours studying or doing homework, being a minority (African American or Latina/o), having higher academic confidence, and having higher mathematics confidence" (Moakler & Kim, 2014, p. 138). Overall, Moakler and Kim's research contributed to the body of research on STEM choice

through highlighting the significant role that self-efficacy can play in STEM major choice.

In specifically focusing on students majoring in engineering, Linda Sax and colleagues (2016) conducted a study examining the determinants of first-year students' plans to major in the field of engineering. Similar to the work of Moakler and Kim (2014), Sax and her colleagues were also guided by SCCT and also used cross-sectional CIRP data. This study selected the intention to major in engineering as the outcome measure for the study and opted for an input-output analytic approach, including personal inputs, background characteristics, learning experiences, self-efficacy, outcome expectations, interests, contextual influences, and choice goals, in a regression analysis (Sax et al., 2015). The results of the study revealed a significant gender gap among college students planning to major in engineering. Furthermore, the study identified predictors of both male and female likelihood of majoring in engineering, including high school GPA, father's occupation, political conservativism, and lower creative and artistic abilities.

One of the first studies to examine high school students' entrance into STEM fields using longitudinal data was a study by Chen and Weko (2009) through the National Center for Education Statistics. This descriptive study used data from the 1995-1996 Beginning Postsecondary Students Longitudinal Study (BPS) in addition to supplemental data from the National Postsecondary Study Aid Study (NPSAS:04) and the Education Longitudinal Study of 2002 (ELS:02). The longitudinal design of this study allowed for the examination of high school student entrance, persistence, and degree completion in STEM fields through postsecondary education (Chen & Weko, 2009). The study itself

was descriptive in nature and focused only on examining the demographic (and non-causal) factors of students entering into STEM fields. It was not guided or informed by conceptual models or theoretical frameworks, and simply examined demographic factors. While the study used longitudinal data and provided insight into the demographics of students entering various STEM fields, Chen and Weko's (2009) research did not examine the *process* of the entry into STEM fields or any additional external, environmental, or cognitive factors influencing that process.

Examining the STEM Major Choice Process

As discussed, most studies have focused on surveying college students already pursuing STEM degrees, and the demographic factors of these students. However, the most prominent research that has recently emerged examining the STEM major choice process for high school students was conducted by Wang (2013a; 2013b). Using nationally-representative longitudinal data from the Educational Longitudinal Study of 2002 (ELS:02) and guided by SCCT, Wang's research sought to understand how high school students make the choice to pursue a STEM degree. In doing so, Wang advanced a model (see Figure 3) in which STEM choice is the result of a process linking together self-efficacy, learning experiences, interest and goals, as well as college readiness. Her study focused on examining the direct and indirect influences of high school exposure to math and science coursework, mathematics achievement, and the intention to major in STEM on a student's entrance into STEM fields of study (Wang, 2013a). As suggested by SCCT, the key factors influencing the choice actions include self-efficacy, outcome expectations, interests, and environmental barriers and supports. Wang also considered that the immediate context and a student's background characteristics play a role in

shaping STEM choice decisions. Wang applied the notion of SCCT's contextual influences proximal to choice behavior in the postsecondary educational context, including expectations, enrollment, remediation, financial aid, and external demands (such as children or work).
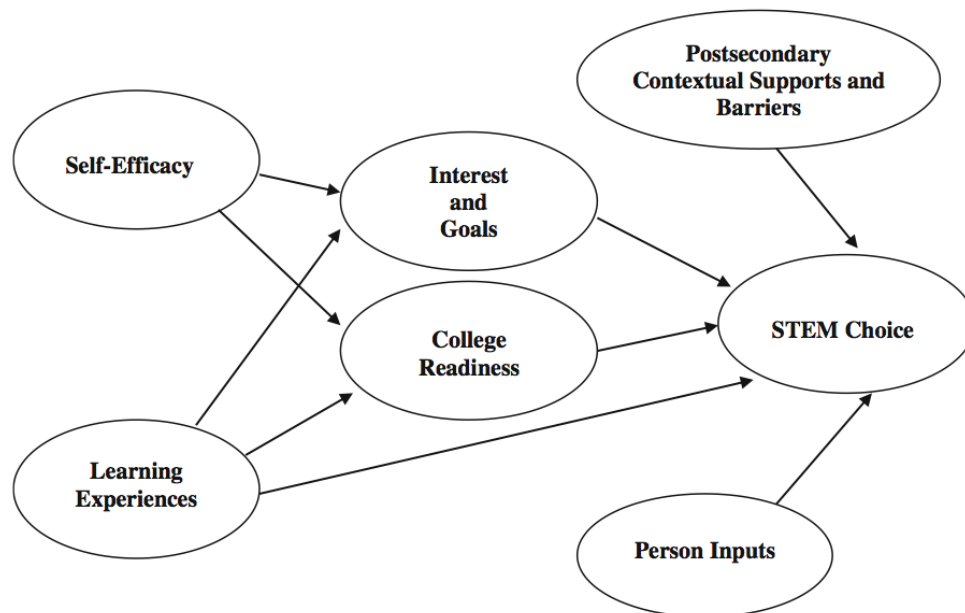
Figure 3: Wang's (2013a) Conceptual Model

The data sample in Wang's study included high school graduates from 2004 who had enrolled in a postsecondary educational institution by 2006. Using confirmatory factor analysis (CFA) and SEM as the selected statistical methods for analysis, Wang tested her proposed conceptual model to examine the relationship among these factors and their impact on entrance into STEM fields in college. When testing the sample as a whole, the fit indices of the SEM analyses suggest an excellent fit of the model to the data. Wang also tested the model by subgroups of race, gender, and SES. The subgroup

testing revealed a multiple-group model based on race and no structural non-invariance across gender and SES, suggesting a hypothesized fit of the model across different subgroups.

The results of the final SEM model suggest that the selection of a STEM major is influenced by the intention to major in STEM, high school achievement, and initial postsecondary educational experiences, with the intention to major having the most significant and positive impact (Wang, 2013a). The results of the study confirmed a direct influence of math achievement, exposure to math and science courses, and self-efficacy in mathematics, on the intention to major in a STEM field. Intention to major in a STEM field is a significant and positive predictor of actual entrance into a STEM field of study. The findings of Wang's study reveal the importance of cognitive and motivational beliefs in the STEM choice process. In addition, the study suggests that postsecondary supports and barriers are critical in students' continued STEM choice throughout postsecondary education.

Wang's (2013a) study was one of the first studies to use nationally-representative longitudinal data to examine the STEM choice process for high school and college students. Through the use of a rich dataset and SEM as the statistical analytic approach, Wang was able to appropriately apply the nature of the SCCT framework in examining the *process* students undergo in selecting a STEM major. In particular, it highlights the significant influence that high school learning in math and science plays throughout the process, implying strong relationships among high school math and science exposure and STEM interest and STEM intention. Wang's work acknowledges the complexity of pathways into STEM majors and the need to better understand the individual,

psychological, contextual, and social influences impacting the STEM choice decision. Her work calls attention to the continued need for investigation of the process for students in the STEM pipeline, emphasizing the importance of high school and postsecondary factors in the decision to pursue a STEM field of study.

<div align="center">**Critique and Methodological Limitations of Prior Work**</div>

This section critiques the work that has been done on this topic and the methodological limitations of prior work. My dissertation study addressed significant gaps in the prior methods of approaching an understanding and conceptualization of the STEM readiness and intention developmental process, through improving methodological components of the statistical analytic approach, the data, and the measures.

Analytic Approach Critique

Neglecting Examination of the Process. With the exception of Nauta and Epperson (2003) and Wang's (2013) work, most studies on STEM choice examine student characteristics and demographic factors that predicted a student's selection of a STEM major. The majority of studies do not examine the *process* involved in students' preparation for and selection of a STEM major during their time in high school. In this approach, previous studies used logistic regression analysis as the statistical method for analysis in their studies (Crisp et al., 2009; Moakler & Kim, 2014; Rogers & Creed, 2011; Sax et al., 2016). While logistic regression is a common technique used to describe data and explain relationships between a dichotomous dependent variable and other independent variables, there are critical limitations with this type of analysis for studies seeking to understand a developmental process.

For example, these previous studies are guided by SCCT, which is based upon the conceptualization of a process unfolding through time. While it makes sense for studies on STEM major choice development to be guided by SCCT, as this theory regards a *process* phenomenon, the selected analytic approach is not best aligned with this framework. When examining processes through time, more complex statistical analyses are necessary to account for the processes and relationships between and among independent variables through time. While previous studies contribute to an understanding of the relationship between the independent variables and the dependent variable, logistic regression and the use of an *input-output* approach is one less suited for examination of such a complex process. More appropriate statistical methods, such as SEM, were necessary address the research questions at hand and provide a more clear interpretation of developmental and decision-making processes.

Sample Selection. In addition to limitations in the approach to examine the developmental process, the appropriate selection of the sample studied is critical. In seeking to understand the process students undergo during high school in the selection of a STEM major, one must include the sample of high school students. The majority of studies conducted on students' entrance into STEM fields (Chen & Weko, 2009; Moakler & Kim, 2014; Sax et al., 2016; Wang, 2013), approach their studies with samples of students who are already admitted to and enrolled in 4-year postsecondary educational institutions. It is important to note that these are studies addressing students who have already successfully made it through the pipeline in selecting and enrolling in a STEM field of study, rather than those who are experiencing the process of major selection earlier in the STEM pipeline.

This sample selection has notable limitations in critical ways: Samples of students already admitted to postsecondary institutions exclude students in high school who are unable to access postsecondary education. According to college access research, barriers to college access could be due to a number of reasons, including financial or informational barriers (Cabrera & LaNasa, 2000; Engle & Tinto, 2008; Perna, 2006). Furthermore, the samples of college students used in these studies exclude many high school students who did not attend a 4-year college. Some students may attend a 2-year institution, a community college, or a technical certification school, while others may opt to delay entrance into postsecondary education immediately following high school graduation. When examining entrance into STEM fields and the developmental process that high school students undergo in deciding to major in a STEM field, it is critical for research to capture the entire high school student population and acknowledge the diverse experiences that take place during high school, as well as the diverse pathways into STEM fields.

Data and Measurement Limitations

Using Cross-Sectional Data. In addition to analytic approach limitations, many previous studies used cross-sectional data, such as first-year student data from the Cooperative Institutional Research Program (CIRP) (Moakler & Kim, 2014; Sax et al., 2016). Cross-sectional data does not allow for the examination of students' experiences through time, but examines different cohorts of students in one segment of time. In addition, cross-sectional assessments that include self-reported retrospective behavior may not be accurate representations of actual longitudinal behavior, and "the use of cross-sectional assessments may lead researchers to draw erroneous conclusions about

student learning and development" (Bowman, 2010, p. 489). Furthermore, the use of cross-sectional data is not aligned with the studies' theoretical framework of SCCT, which follows students' developmental process through time. Longitudinal data, which tracks students' behaviors, actions, and experiences over an extended period of time, allows for the examination of a complex process unfolding through time. Because of this, the use of longitudinal data is more appropriate when examining developmental and decision-making processes as it can account for actual behaviors and actions over a period of time. Lent et al. suggests in numerous studies (2003; 2008a; 2008b) that longitudinal data is necessary for testing of the SCCT model, calling attention to the need for more studies to adopt this recommendation.

Measuring STEM Self-Efficacy. While the work of Wang (2013a) *does* use longitudinal data from the Educational Longitudinal Study of 2002 (ELS:02) to model the selection of a STEM major, the measurements used from the data are limited in important ways. Wang's study was somewhat limited in providing adequate measures of STEM-related content. For example, because the survey design of ELS:02 only included survey items related to self-efficacy in mathematics, the construct of self-efficacy could only be conceptualized using measures of math self-efficacy. SCCT suggests that self-efficacy is a dynamic belief that varies across different fields or domains. Wang's study is limited in capturing the extent to which a student feels self-efficacious in subjects beyond mathematics. Because science is a key subject in STEM fields of study, including science self-efficacy as a measure of self-efficacy is important in understanding the impact of this cognitive component on the career development process. Similarly, while Moakler and Kim (2014) appraised self-efficacy through two measures of self-confidence (one in

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mathematics ability and one in academic ability), the measure of self-efficacy in their

study did not include indicators of self-efficacy in science content. The authors address

the absence of science self-efficacy in their limitation section as a notable constraint of

the CIRP database and in their analysis. Including additional and more nuanced measures

of self-efficacy in the academic areas of math and science (in relation to course content,

textbooks, skills, etc.) may better capture the complexity of STEM self-efficacy.

In addition to critiques in measurement, there are some limitations in the model of

SCCT in regards to influences on self-efficacy. Lent et al.'s (1994) model of SCCT is

limited in illustrating the relationship between self-efficacy and familial factors impacting

the career development process. While Lent and his colleagues emphasize self-efficacy as

a key component influencing this development process, the theorists have not included in

their model the ways in which self-efficacy can be impacted by familial and/or parental

factors. According to previous research, self-efficacy can be directly affected by external

influences, such as parents, teachers, and peers (Bandura, 1993; Bandura, Barbaranelli,

Caprara, & Pastorelli, 2001; Caprara, Barbaranelli, Steca, & Malone, 2006; Zimmerman,

Bandura, & Martinez-Ponz, 1992). Though Lent and his colleagues include background

contextual influences and personal inputs, they suggest that these are all mediated

through learning experiences, which impacts self-efficacy. This theoretical framework

does not account for the *direct* impact of parental influence or the impact of students'

ability on his or her self-efficacy. Previous research on self-efficacy provides evidence

for the relationship between self-efficacy and parental involvement (Alliman-Brisset,

Turner, & Skovholt, 2004; Ferry, Fouad, & Smith, 2000; Turner & Lapan, 2002) and

self-efficacy and ability (Bandura, 1993; Bell & Kozlowski, 2002; Hackett, 1985; Pajares

& Kranzler, 1995). However, these relationships are not currently reflected in the model of SCCT.

Measuring STEM Interest. The extant literature on the STEM choice process is also limited by neglecting inclusion of measures of students' interest in STEM-related content. Career interests can be defined as a fluid development of interests in regards to skills, tasks, and activities related to a particular field or domain. Social cognitive career theorists suggest that practice, exposure to activities, refinement of skills, self-efficacy, and outcome expectations contribute to the development of career-related interests (Lent et al., 1994). According to SCCT, interest directly impacts goals related to career choice and planning.

In regards to interest in STEM-related content, previous research has measured STEM interest as one's career intention in a STEM field (Sadler et al., 2012), the perceptions of supportive environments in science careers, the interest in pursuing educational opportunities to lead to a career in science, and the perceived importance of a career in science (Tyler-Wood, Knezek, & Christensen, 2010). The National Center for Education Statistics has also considered math and science interest as the extent to which a student enjoys the math and/or science subject (Ingels et al., 2011). As emphasized by previous research, STEM interest is one of the most important factors directly impacting a high school students' selection of a career in STEM (Hall et al., 2011; Lent et al., 1998; Seymour & Hewitt, 1997).

Despite ways in which STEM interest has been previously assessed and the impact interest has on career selection, research related to studying the STEM readiness and intention process does not fully capture or include the construct of STEM interest

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(Moakler & Kim, 2014; Wang, 2013a). This limits the extent to which previous work

includes key components impacting the intention to major in a STEM field. In Wang's

(2013a) study, interest in math is included as a factor. However, the study does not

include interest in science-related content. Her decision to do this is likely due to

limitations in available measures or items in the dataset related to student interest in

science. Not including a measure of science interest limits the extent to which this

construct fully captures a student's interest in STEM career-related content, as well as the

extent to which conclusions can be drawn about the relationship between interest with

other key factors in the STEM readiness and intention development process. Further

research would be necessary to improve upon the measures of interest to extend beyond

interest in solely mathematics.

   Measuring Parental Influences. Previous research suggests that parental

involvement, encouragement, and support play a critical role in the college and career

development and decision-making process (Cabrera & LaNasa, 20000; Fan & Chen,

2001; Ferry, Fouad, & Smith, 2000; Jeynes, 2007; Keller & Whiston, 2000). Though

SCCT also suggests that background contextual affordances, such as parental support and

encouragement, impact the college and career development process, previous research

does not include parental involvement as an influential factor (Moakler & Kim, 2014;

Sax et al., 2016; Wang, 2013a). Wang's STEM choice model does not include parental

involvement. This important influence has also been documented to have a key influence

on the development of self-efficacy (Alliman-Brisset, Turner, & Skovholt, 2004; Ferry,

Fouad, & Smith, 2000; Turner & Lapan, 2002). To this end, previous research related to

STEM readiness and intention development is notably limited in including measures of

parental influence and ascertaining the extent to which this factor plays a role in the process through impacting self-efficacy, STEM readiness, and the intention to major in a STEM field.

Addressing Gaps

This dissertation study sought to overcome the series of limitations discussed from the extant literature regarding the analytic approach, data, and measurement considerations in studying the STEM readiness and intention development process among high school students.

Analytic Approach

Statistical Technique. The majority of studies on the STEM major choice process have opted for the use of various forms of regression analysis to examine what we understand to be a complex developmental *process.* In contrast, I used SEM as the statistical analysis technique. This technique allowed me to gain a deeper understanding of the STEM intention development process and the relationships among factors influencing this process. SEM, which is explained in more detail in Chapter 3, is a statistical analysis approach allowing for the examination of a complex process unfolding over time (Byrne, 2013; Kline, 2015). Commonly used in social sciences, SEM allows for the testing of latent constructs (such as cognitive concepts of self-efficacy) and the relationships among various measured factors throughout a longitudinal process (Anderson & Gerbing, 1988). As such, in understanding the complex nature of influential factors on this process, I acknowledge SEM as the most appropriate method for testing a conceptual model of this process.

Sample Selection. Furthermore, while previous research (Chen & Weko, 2009;

Moakler & Kim, 2014; Sax et al., 2016; Wang, 2013) focused on sampling college students at 4-year institutions, my dissertation study focused on examining the experiences of all high school students, including those who may not have had access to postsecondary education. Through not limiting to students already in postsecondary education, I was able to include high school students who may not have entered college immediately following high school, those who attended a 2-year or technical postsecondary educational institution, and those who may have faced financial or other barriers prior to ultimately enrolling in college. To answer the research question seeking to understand the STEM readiness and intention development process for high school students, it is critical to fully capture the high school student body. Thus, I opted to use a data sample capturing a nationally-representative cohort of *all* high school students in our nation from the time they were in 9th grade through their 12th grade year in high school.

Data and Measurement

Longitudinal Data. In order to overcome the problems associated with the use of cross-sectional data, I opted to use the most recent nationally-representative longitudinal database: the High School Longitudinal Study of 2009 (HSLS:09). Longitudinal databases, such as HSLS:09, account for the limitation many previous studies face in their use of cross-sectional data (Crisp et al., 2009; Moakler & Kim, 2014; Lent et al., 2003; 2008; Sax et al., 2016). When examining a process, such as the college or career decision-making process, the use of longitudinal data is regarded as the most appropriate approach for such studies (Singer & Willett, 2003). Through the use of longitudinal data my dissertation study was able to more appropriately examine the STEM readiness and intention development *process* unfolding through time.

Improved Measures. Furthermore, not only is HSLS:09 the most recent nationally-representative longitudinal database, it is unique in its survey design in comparison to previous national educational longitudinal surveys through inclusion of numerous survey items directly related to STEM content. This inclusion of STEM-relevant items allowed for a more precise measure of student academic performance in and exposure to STEM-related content, as well as a more nuanced understanding of self-efficacy and interest in STEM-related fields.

In addressing the limitations of previous research in measuring STEM self-efficacy, this dissertation study appraised self-efficacy in mathematics *as well as* self-efficacy in science. Through including self-efficacy in science alongside self-efficacy in math, as Wang's (2013a) study addressed, my dissertation study sought to better capture this cognitive component in relation to the STEM subject matter, as science is a significant academic subject for both preparation for and success in STEM fields (Sadler, Sonnert, Hazari, & Tai, 2012; Tyson, Lee, Borman, & Hanson, 2007).

The majority of research studies conducted on entrance into STEM fields excludes measures of interest in STEM-related content. This dissertation study not only included STEM interest as a critical factor impacting the STEM development process, but also improved upon the measurement of interest in STEM fields, through the use of items measuring students' interest in both math- and science-related content during high school.

This dissertation study filled an important gap in the work of Wang (2013a) and Moakler and Kim (2014) by including parental involvement as a key factor in the consideration of a STEM major. Given the importance of parental involvement in the

college and career development decision-making process, this study appropriately

reflected a model of STEM readiness and intention development through inclusion of

parental involvement as a key factor impacting the process.

The Proposed Conceptual Model

Overview

In my dissertation study, I proposed a new conceptual model for understanding

the STEM readiness and intention development process, which I term the *STEM*

Readiness and Intention Development (SRID) Conceptual Model (see Figure 1). While

guided by SCCT, the SRID model also integrates many components of Wang's (2013a)

conceptual model of STEM choice. As previously discussed, SCCT emphasizes the

interaction within and among the cognitive concepts (including self-efficacy, interests,

and goals), as well as the impact of the personal inputs and contextual influences

(including background contextual factors and contextual influences proximal to choice

behaviors).

Cognitive Components. SCCT acknowledges self-efficacy as one of the key

components of social cognitive theory and a significant factor in career development and

career decision-making. Accordingly, the SRID conceptual model includes STEM self-

efficacy as a key component in the STEM readiness and intention development process.

Other cognitive components of the SCCT theory include outcome expectations, interests,

and goals. SCCT emphasizes the formation and elaboration of career-relevant interests,

and acknowledges interest as a direct factor on the career development and decision-

making process (Lent et al., 1994). Aligned with SCCT and Wang's (2013) conceptual

model, my SRID model includes STEM interest as another key component in the

developmental process.

Wang's (2013) conceptual model draws attention to the importance of college readiness in the selection of a STEM major. Guided by Wang's inclusion of college readiness in her conceptual model, the SRID model incorporated a STEM-specific construct of readiness, termed STEM readiness. STEM readiness is also an operationalization of SCCT's construct of *learning experiences*, as it includes high school students' exposure to and performance in STEM-related coursework. Aligned with SCCT and Wang's conceptual model, my proposed model suggests a direct effect of STEM readiness on the intention to major in a STEM field of study.

The outcome variable in my proposed conceptual model, intention to major in STEM, can also be considered a cognitive component aligned with SCCT. Lent et al. (1994) regard goal-setting as key component in the cognitive career selection process, defined as cognitive components which guide actions and behaviors. In the model of SCCT (see Figure 2), goals directly follow interests and immediately proceed action. According to SCCT, intention to major in STEM may also be considered as a more action-oriented cognitive concept, indicating a planned behavior or follow-through action related to the goal of majoring in a STEM field. Wang's (2013) model also includes the intention to major in STEM as a key factor in the STEM choice process, with her findings suggesting intention to major as having the most significant influence on actual entrance into STEM fields. As such, my model includes intention to major as the main outcome variable.

Contextual Components. According to SCCT, *background contextual factors* include one's interaction with their own culture and the ways in which their self-concept

and learning experiences have been impacted through socialization (Lent et al., 1994). As such, my proposed conceptual model represents background characteristics through socioeconomic status (SES) which includes parental education and family income. SCCT also recognizes *personal inputs* as significant factors influencing this developmental process. For example, a student's natural abilities in mathematics may predispose him or her to engage more positively in learning experiences relevant to the use of mathematics skills. Aligned with SCCT, my proposed model includes mathematics ability as a personal input.

According to Lent and associates, *contextual influences proximal to choice behavior* are directly related to career choice concerns, such as career network contacts, role models, or external barriers (Lent et al., 2003). These proximal environmental factors moderate the relation of interests to choice goals, as well as the relation of goals to actions. For example, Lent and colleagues (2003) suggest that influential role models or familial involvement and acculturation may directly influence individual's own career choices, perhaps more strongly than personal career interests. In my SRID conceptual model, I interpret parental involvement as a key *contextual influence proximal to choice behavior*, and represent this factor in the model accordingly.

[Figure 1 on next page]
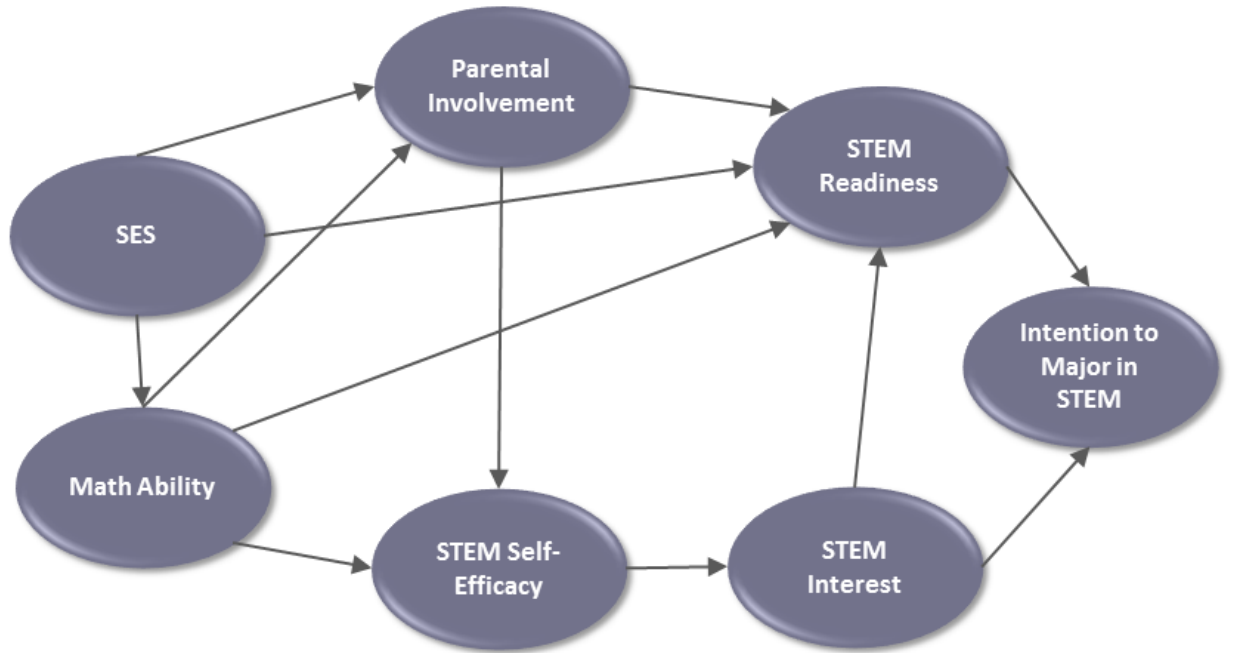
Figure 1: The STEM Readiness and Intention Development (SRID) Conceptual Model[2]

Factors in Proposed Conceptual Model

Drawing upon relevant literature from both higher education and career

development research, this section of the literature review highlights the most important

factors impacting the STEM readiness and intention development process. Most

importantly, this section emphasizes the empirical evidence supporting the selection of

these factors, as well as the reasoning for their incorporation within the SRID conceptual

model. These influential factors, including SES, mathematics ability, parental

involvement, STEM self-efficacy, and STEM interest, have been documented to

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[2]As illustrated, the STEM Readiness and Intention Development Conceptual Model suggests that SES impacts both mathematics ability, parental involvement, and STEM readiness. Mathematics ability impacts STEM self-efficacy and parental involvement. In turn, parental involvement impacts STEM self-efficacy and STEM readiness. As supported by SCCT and previous research using the SCCT model, I predicted that STEM self-efficacy had an indirect effect on students' intention to major in STEM as mediated through the direct impact of STEM interest on intention to major in STEM. My model also suggests that STEM interest impacts STEM readiness, which has a direct impact on intention to major in STEM.

influence the STEM readiness development process and students' intention to major in a STEM field.

Socioeconomic Status

Socioeconomic status (SES) is a measure of economic and sociological standing in society, commonly measured by a combination of income, occupation, and/or education (Cowan et al., 2012). SES has been continually emphasized in education research as a key component in academic preparation and overall educational achievement (Cabrera & LaNasa, 2000; Lee & Burkam, 2002; Perna, 2005; Rowan-Kenyon, 2007; Sirin, 2005; White, 1982). In relation to college major choice, Ma's (2009) study highlights the significant role that SES plays in students' selection of a college major. This particular study, which examined nationally representative longitudinal data, found that children from lower SES families were more likely to select college majors in lucrative careers, emphasizing the role SES can play throughout the career development process (Ma, 2009). In recognizing the importance that school context may play in this process, the measure of SES may account for the role of class and community context in relation to the school's social and economic resources (Portes & MacLeod, 1996).

Additional research highlights the direct impact that SES has on math ability (Lee & Burkam, 2002; Reyes & Stanic, 1988; Sirin, 2005), parental involvement (Eagle, 1989), as well as STEM readiness (i.e. the extent to which a student becomes prepared for a STEM field of study) (Cabrera & LaNasa, 2000; Hoffer, Rasinski, & Moore, 1995; Lee & Burkam, 2002; Perna, 2006). Previous research also suggests a significant connection between SES and parental involvement. In particular, previous work suggests

that SES impacts the extent to which parents are involved in their students' schooling and educational experience (Eagle, 1989; Leppel, Williams, & Waldauer, 2001; Ma, 2009). The SRID conceptual model draws on the findings of previous research, with SES directly impacting math ability, reflecting the direct impact that SES has on math ability, parental involvement, and STEM readiness.

Mathematics Ability

Mathematics ability has been recognized as an important factor in educational achievement and college readiness (Cabrera & LaNasa, 2000; Conley, 2007; Perna, 2005; Rohde & Thompson, 2007). In relation to familial impact, ability has been studied as a predictor of the extent to which a parent is involved in the educational experience of their child (Eccles & Harold, 1993; Patel & Stevens, 2010). Rohde and Thompson (2007) assert the relationship between abilities and student performance and achievement in academic settings, suggesting an important link between cognitive ability and academic achievement. Ability is also directly linked to students' feelings of self-efficacy, particularly in the areas of math and science (Bandura, 1993; Bell & Kozlowski, 2002; Hackett, 1985; Pajares & Kranzler, 1995). For example, students with stronger abilities in mathematics have a greater sense of self-efficacy in mathematics.

Furthermore, mathematics ability impacts the extent to which students meet benchmarks to become academically prepared for a STEM field of study (Hackett, 1985; Rohde & Thompson, 2007; Spinath, Spinath, Harlaar, & Plomin, 2006). Literature on college access and choice emphasize the importance of math ability in college readiness, specifically in the academic courses taken and the high school grade point average earned (Conley, 2007). Supported by this previous research, the SRID conceptual model

acknowledges the importance of math ability and emphasizes the impact of math ability on parental involvement, self-efficacy, and STEM readiness.

Parental Involvement

Parental involvement can be defined as the extent to which a parent is involved in a child's academic and schooling experience, which has been strongly related to students' overall educational experience and academic achievement (Cabrera & La Nasa, 2001; Fan & Chen, 2001; Hill & Tyson, 2009; Jeynes, 2007; McNeal, 1999; Reynolds, 1992). In particular, Cabrera and LaNasa (2001) suggest that the behavioral dimension of parental involvement on students' educational experiences is strongly associated with high school students' academic achievement (Fan & Chen, 2001; Jeynes, 2007; Perna & Titus, 2005; Stewart, 2008). In a study guided by SCCT, Ferry, Fouad, and Smith's (2000) work emphasizes the critical role that the familial context has on career choice behavior. Furthermore, Keller and Whiston (2008) suggest that for young adolescents in particular, parental influences play a critical role impacting their career development. The extensive meta-analysis conducted by Hill and Tyson (2009) reveal that the type of parental involvement is also critical. They identified three broad categories of parental involvement in schooling, including 1) *academic socialization*, 2) *home-based involvement*, and 3) *school-based involvement*. Their findings suggest that parental involvement that reflects academic socialization, which includes communication about parental expectations for education and discussing the future, has the strongest impact on students' academic achievement (Hill & Tyson, 2009).

In regards to STEM career choice, Hall et al. (2011) highlighted parental influence as one of the top four influences on STEM career choice among high school

students. In light of these findings, my conceptual model addressed gaps in previous work (Moakler & Kim, 2014; Sax et al., 2016; Wang, 2013) through incorporating parental involvement into this model as a key factor in STEM readiness and intention development.

Accordingly, my model of SRID suggests that in development of STEM intention, parental involvement impacts STEM self-efficacy and STEM readiness. Previous research suggests that self-efficacy is directly impacted by the extent to which parents are supportive and involved in their student's academic and schooling experience (Alliman-Brisset, Turner, & Skovholt, 2004; Ferry, Fouad, & Smith, 2000; Turner & Lapan, 2002). In addition, Ferry, Fouad, and Smith's (2000) study found that parental involvement had a significant effect on the number of math and science courses taken and the grades earned in those math and science courses. As such, my conceptual model improves upon previous models on the STEM major choice process through highlighting the relationships between parental involvement and SES, math ability, STEM self-efficacy, and STEM readiness.

STEM Self-Efficacy

Self-efficacy can be defined as one's belief in his or her ability to succeed in accomplishing a task (Bandura, 1977). It is often interpreted as one's mastery of experiences and skills, and confidence in one's ability to perform and succeed (Bandura, 1994). In his social cognitive theory, psychologist Albert Bandura theorized that self-efficacy could be developed through external and environmental experiences, which ultimately impact feelings and behaviors. Self-efficacy impacts the ways in which individuals view their abilities and capabilities, which affects performance, interests, and

behaviors. Social cognitive theorists suggest that self-efficacy can be a changing set of beliefs about oneself, dependent on the context and the situation, such as the nature of the tasks, one's social and environmental surroundings, and one's feelings of competence on similar tasks (Bandura, 1977; Lent et al., 1994; Sharf, 2013; Zimmerman, 2000). In the academic context, students with high self-efficacy may be more likely to become interested in course content, more likely to set higher academic goals, and thus more likely to achieve those goals (Lent, Brown, & Larkin, 1984; Multon, Brown, & Lent, 1991; Zimmerman, Bandura, & Martinez-Pons, 1992).

Self-efficacy theories have been applied in career development theory to interpret influences on career choice behavior[3] (Bandura, 1994; Hackett & Betz, 1995; Lent et al., 2003; Rittmayer & Beier, 2008). SCCT suggests that self-efficacy has a direct effect on achievement and strongly influences ultimate career selection[4]. However, SCCT does not include the direct impact of familial contextual factors on self-efficacy. According to previous research, self-efficacy can be directly affected by external influences, such as parents, teachers, peers, etc. (Bandura, 1993; Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Caprara, Barbaranelli, Steca, & Malone, 2006; Zimmerman, Bandura, & Martinez-Ponz, 1992). Though the SCCT model includes *background contextual influences* and *personal inputs*, these are all mediated through *learning experiences*

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[3] Betz and Hackett's (1986) research applied self-efficacy theory specifically to interpret gender disparities in the labor work force. Their work emphasizes the usefulness of self-efficacy theory in career development theory in predicting the career decision-making process for men and women, through identifying gender differences in self-efficacy impacting occupational choice (Betz & Hackett, 1986). Since this foundational study, several studies have supported the findings of the significance of self-efficacy in the career decision-making process.

[4] In 2003, Lent and colleagues applied Social Cognitive Career Theory (SCCT) and Bandura's (1999) social cognitive theory in examining students majoring in engineering. Through testing social cognitive models on the sample of engineering students, the study provided support for a model that portrays contextual supports and barriers indirectly linked to goals and actions through self-efficacy (Lent et al., 2003).

which impacts self-efficacy. In regards to self-efficacy, SCCT does not account for the impact of parental influence or students' ability on his or her self-efficacy. Previous research provides evidence for a direct relationship between self-efficacy and parental involvement and self-efficacy and ability (Bandura, 1993; Turner & Lapan, 2002). In particular, self-efficacy is directly impacted by the extent to which parents are supportive and involved in their student's academic and schooling experience (Alliman-Brissett, Turner, & Skovholt, 2004; Ferry, Fouad, & Smith, 2000; Turner & Lapan, 2002). Additionally, ability impacts the extent to which a student feels self-efficacious (Bandura, 1993; Bell & Kozlowski, 2002; Greene, Miller, Crowson, Duke, & Akey, 2004; Hackett, 1985; Nauta & Epperson, 2003; Pajares & Kranzler, 1995).

Accordingly, my conceptual model incorporates self-efficacy as a key cognitive factor impacting the STEM readiness and intention development process. Building upon SCCT, my model acknowledges that self-efficacy is also related to other important contextual factors in the development process. In particular, my model accounts for the impact of parental involvement on self-efficacy. It also recognizes the fact that self-efficacy can be affected by mathematics ability throughout the STEM readiness and intention development process.

Furthermore, my model of SRID acknowledges the relationship between self-efficacy and interest (Bandura & Schunk, 1981; Lenox & Subich, 1994; Rottinghaus, Larson, & Boren, 2003), particularly for adolescents in high school (Bandura, 2006; Pajares, 2006). SCCT theorists suggest that self-efficacy strongly mediates through interest, with interest being a strong predictor of career choice (Lent et al., 2001; 2003; Nauta, 2004; Nauta & Epperson, 2003; Scarf, 2013). This suggests that self-efficacy may

have an indirect impact on STEM readiness and the intention to major in STEM, as mediated through STEM interest.

STEM-Specific. In addition to acknowledging the relationships that exist between self-efficacy and other key factors in the process, the SRID conceptual model contributes to refining the understanding of self-efficacy as it relates to STEM readiness and intention development. In particular, my model appraises the content of STEM self-efficacy, extending this concept to specific domains of efficacy - especially in the field of mathematics. When studying self-efficacy in relation to STEM, researchers have examined the impact of self-efficacy in mathematics (Bandura, 1993; Betz & Hackett, 1983; Lent, Lopez, & Bieschke, 1991; Pajares, 2005; Rittmayer & Beier, 2008). Previous research suggests that mathematics self-efficacy is critical in the selection of STEM majors, in fields such as mathematics, engineering, physics, and science (Betz & Hackett, 1983; Hackett, 1985; Hazari, Sonnert, Sadler, & Shanahan, 2010; Lent et al., 1991; Wang, 2013a). Though the majority of these studies have linked mathematics self-efficacy to the selection of STEM-related careers, few scholars (Britner & Parjares, 2006) have examined self-efficacy in science.

Given the extensive research on self-efficacy theory, it is well understood that there are important relationships between self-efficacy and academic performance and between self-efficacy and goal-setting. SCCT suggests that self-efficacy is a dynamic belief that varies across different fields or domains. When examining students becoming prepared for a STEM career and considering selection of a STEM major, it is imperative to also consider the impact of self-efficacy in other domains of STEM fields, beyond solely mathematics. Though studies have separately examined self-efficacy in

mathematics and self-efficacy in science, there has been limited research examining both forms of self-efficacy simultaneously. My conceptual model considered measuring self-efficacy in both math and science in an effort to better capture the concept of STEM self-efficacy.

STEM Interest

STEM interests can be defined as interest in skills, tasks, and activities related to the fields and domains of science, technology, engineering, and mathematics. In the area of career development research, interest in general is acknowledged as an important factor in career choice. Psychologists in the early to mid-1900s began to grapple with the cognitive conception of "interest" and its relation to one's identity and one's conception of self (Cole & Hanson, 1974). Cole and Hanson's (1974) study related this concept of interest inventories on career selection, focusing specifically on the differences between men and women. Though the work of Cole and Hanson may be dated in terms of gender studies, it draws attention to the importance of considering individual interests on one's process of selecting a career, acknowledging the simplicity and significance of individuals selecting careers with which they would be most personally satisfied.

SCCT incorporates the impact of interest into the model of career choice. This emphasizes the formation and elaboration of career-relevant interests, and acknowledges interest as a *direct* factor on the career development and decision-making process (Lent et al., 1994). Seymour and Hewitt's (1997) work reveals the important relationship between interest in math- and science-related content and a student's decision to pursue a career in a STEM field. The research of Sadler, Sonnert, Hazari, and Tai (2012) addressed the possible stability and volatility of interest in STEM careers throughout high school. Their

findings suggest that early career interest in STEM-related content is the strongest predictor of career interest when leaving high school, emphasizing the critical nature of early experiences, socialization, and career interest development by the end of high school (Sadler et al., 2012). In addition, Hall et al.'s (2011) study found that when supported by parents or teachers, high school students' interest in STEM and STEM occupations influenced career choice in STEM, and was one of the top four factors impacting this decision.

As suggested and supported by previous research (Hall et al., 2011; Lent et al., 1994; Sadler et al., 2012; Seymour & Hewitt, 1997), my SRID model incorporated STEM interest as an influential factor directly impacting intention to major in STEM. Moreover, in improving upon previous work (Wang, 2013a), my study incorporated measures of interest in both mathematics and science-related content. My conceptual model is aligned with SCCT and Wang's conceptual model in that it acknowledges the direct relationship between interest and intention to major in STEM. In addition, my model incorporates the relationship between STEM interest and the extent to which students become academically prepared for a STEM field of study. Previous research suggests that interest in academic content has an impact on academic achievement (Schiefele, Krapp, & Winteler, 1992; Singh, Granville, & Dika, 2002) and course-taking plans (Lent, Brown, & Hackett, 1994; Thorndike-Christ, 1991; Updegraff; Eccles; Barber, & O'Brien, 1996), particularly in the areas of math and science. These are both important components in what has been conceptualized as *STEM readiness* (Mattern et al., 2015), which will be explored in the next section.

STEM Readiness

For decades, higher education research has focused on defining and understanding what it means for students to be prepared for college. Being prepared for college has been termed by many researchers in the field of higher education as *college readiness*, which can be defined by the achievement of benchmarks signifying academic preparation for success in college (Berkner & Chavez, 1997; Cabrera, Burkum, & LaNasa, 2005; Calcagno, Crosta, Bailey, & Jenkins, 2007; Wiley, Wyatt, & Camara, 2011). Research in the area of college readiness has focused on the various pathways to postsecondary education and in outlining the predictors of success for enrollment in and persistence through college. College Board's 2011 research report on college readiness address the characteristics associated with college readiness, including SAT scores, high school grades, and the rigor of academic coursework (Wiley et al., 2011). Metrics such as high school grade point average, college entrance exam scores, class rank, and academic coursework have been associated with predicting success in college and qualifying college readiness (Berkner & Chavez, 1997).

With the increasing importance of strengthening the academic pipeline to STEM careers, researchers at ACT have developed benchmarks for students to be deemed "ready for STEM" (Mattern, Radunzel, & Westrick, 2015, p. 2). The recent ACT report, written by Mattern, Radunzel, and Westrick (2015), states that STEM readiness is considered to be more specific than college readiness. Therefore, specific benchmarks for STEM readiness have been proposed, revolving around achievement in mathematics and science. Because STEM majors and fields often demand skills, abilities, and a strong knowledge base in mathematics and science (Goldman, Schmidt, Hewitt, & Fisher, 1974;

Chen & Weko, 2009; Crisp, Nora, & Taggart, 2009; Westrick, 2015; Whalen & Shelley, 2010), STEM readiness benchmarks revolve around high achievement in these subjects. For example, typical college readiness benchmarks, such as having completed Algebra II (Perna, 2015; Reid & Moore, 2008; Roderick, Nagaoka, & Coca, 2009), may not be considered an adequate indicator for readiness and success in a STEM major (Mattern et al., 2015). Research indicates that preparation for education and careers in STEM-related fields requires higher levels of mathematics and science knowledge and skills (Mattern et al., 2015; Westrick, 2015). Chen's (2013) research for the National Center for Education Statistics also supports these findings, suggesting that students who earn more credits in STEM-related courses and perform well academically in these courses are more likely to succeed in STEM majors. The ACT report affirms that academic achievement and preparation in STEM are imperative for readiness to succeed and persist in STEM education and STEM fields (Mattern et al., 2015). In particular, the mathematics and science courses taken as well as the academic performance in STEM-related course content are key benchmarks in STEM readiness. According to Sadler, Sonnert, Hazari, and Tai (2012), achievements of these benchmarks is a significant predictor of a sustained interest in STEM by the end of high school, implicating likelihood for career choice and goal setting in a STEM field. Research has also revealed a link between math and science coursework taken in high school and future degree attainment in a STEM major (Tyson, Lee, Borman, & Hanson, 2007).

My conceptual model of SRID accounts for the influence of STEM interest on STEM readiness. In addition, this conceptual model illustrates the relationship of STEM readiness with several influential factors in high school students' intention to major in

STEM, including SES, math ability, and parental involvement. As emphasized in college access and choice literature, there is a significant relationship between SES and academic achievement (Cabrera & LaNasa, 2000; Lee & Burkam, 2002; Perna, 2006; Sirin, 2005; White, 1982). In addition, SES impacts the extent to which high school students select courses in mathematics and science (Hoffer, Rasinski, & Moore, 1995). Since these are acknowledged by the literature as benchmarks in STEM readiness, my conceptual model illustrates a direct impact of SES on STEM readiness. In alignment with the ACT report (Mattern et al., 2015), my model recognizes that valid indicators of STEM readiness should include measures such as high school grade point average and credits earned in STEM-related coursework.

STEM readiness is also impacted by students' math ability (Hackett, 1985; Rohde & Thompson, 2007; Spinath, Spinath, Harlaar, & Plomin, 2006). Rohde and Thompson (2007) make an important link between cognitive ability and academic achievement, asserting the relationship between abilities and student performance and achievement in academic settings. Literature on college access and choice emphasize the importance of math ability in college readiness, specifically in the academic courses taken and high school grade point average earned (Conley, 2007). Though the relationship between math ability and achievement of benchmarks in STEM readiness is more intuitive, this model acknowledges that students with stronger math abilities may be more likely to take quantitative-based courses in high school, including math and science classes, and would be more likely to earn a higher grade point average in these courses than students with a lower math ability.

College access and choice research highlights the significant role that parents and

the familial context play in students' academic achievement and college preparation

(Cabrera & LaNasa, 2000; Fan & Chen, 2001; Jeynes, 2007; Tierney & Auerbach, 2005).

In the context of career choice behavior, Ferry, Fouad, and Smith's (2000) study found

that parental encouragement had a significant effect on the number of math and science

courses taken and the grades in those math and science courses[5], which is aligned with

the benchmarks for STEM Readiness (Mattern et al., 2015). As such, my proposed

conceptual model illustrates a direct relationship between parental involvement and

STEM readiness.

In summary, the SRID conceptual model recognizes the centrality of STEM

readiness in the process high school students undergo in intending to major in STEM. My

model acknowledges that a student's behaviors, such as course-taking and achievement,

are impacted by the cognitive components of self-efficacy and interest throughout high

school. Ultimately, STEM readiness mediates many influences on its direct impact on

intention to major in a STEM field.

Intention to Major in STEM

The *intention to major in STEM* can be defined as the consideration of a major in

a STEM field of study in postsecondary education. Intention to major in STEM may also

be regarded as a planned behavior, comparable to goal-setting in the SCCT model. Lent

et al. (1994) regard goal-setting as key component in the cognitive career selection

process, defined as cognitive components which guide actions and behaviors. In the

model of SCCT, goals directly follow interests and immediately precede action. Guided

by SCCT, intention to major in STEM may also be considered as a more action-oriented

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[5] Ferry, Fouad, and Smith (2000) conceptualized these items as a construct of "learning experiences."

cognitive concept, indicating a planned behavior or follow-through action related to the goal of majoring in a STEM field.

In the SRID conceptual model, intention to major in STEM was selected as the main outcome measure due to its important relationship to high school students' entrance into STEM fields in postsecondary education. According to Wang's (2013a) model, choosing a major in STEM is directly influenced by the intention to major in STEM, with the intention to major exerting the largest impact on actual entrance into STEM fields. This finding is aligned with Ajzen's (1991) theory of planned behavior, which suggests that intentions are regarded as predictors for actual behavior. This relationship is also supported by results from the American Freshman: National Norms survey[6], which proves intentional major selection to be an accurate depiction of trends in degree fields several years later (National Science Foundation, 2014). Furthermore, the study conducted by Mattern et al. (2015) for the recent ACT report on developing STEM readiness benchmarks revealed that a student's intention to major in a STEM field as a high school student as well as their measured interest in STEM contributed to the prediction of success in STEM major degree completion.

As suggested by previous research, intention to major in STEM is regarded as an important factor related to both entrance into and success in STEM fields of study. My proposed conceptual model draws attention to the ways in which key factors throughout the high school experience influence students' intention to major in a STEM field. In alignment with previous research, my conceptual model of SRID reflects the important

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[6] The American Freshman: National Norms survey, which is administered by the Higher Education Research Institute at the University of California – Los Angeles, surveys large numbers of students about their intended majors in postsecondary education.

relationship between STEM interest and intention to major in STEM (Hall et al., 2011; Lent et al., 1994; Sadler et al., 2012; Seymour & Hewitt, 1997; Wang, 2013a), as well as between STEM readiness and intention to major in STEM (Mattern et al., 2015; Sadler et al., 2012; Tyson et al., 2007).

Chapter Summary

This chapter highlighted and reviewed notable research on students' decision to pursue a degree in a STEM field, the factors contributing to that decision, and what is known and unknown about the STEM readiness and intention development process. In particular, this chapter addressed research related to this process among high school students and the ways in which research on this topic has been approached. Through this review, I identified several methodological limitations in the current body of literature, including limitations in analytic approach, data, and measurements. The identification of gaps in previous research highlighted the need for continued investigation in this area, as well as ways to address existing limitations. After identifying the ways my dissertation study approached these gaps, I introduced my conceptual model of SRID. This conceptual model was guided by the theoretical framework of SCCT and based upon previous research conducted on entrance into STEM fields. In describing and explaining tenants of the model, I reviewed research on each factor within the model, including SES, mathematics ability, parental involvement, STEM self-efficacy, STEM interest, STEM readiness, and the intention to major in STEM. This review identified key research studies supporting the reasons for including these factors in the model, as well as for supporting the relationships among the factors with one another and to the STEM readiness and intention development process.

Chapter III: Methodology

This chapter seeks to address gaps to explain the process high school students undergo in their intention to pursue a STEM major by advancing a conceptual model. After an overview of the purpose of this study, this chapter briefly describes the proposed model guiding the study: the *STEM Readiness and Intention Development (SRID) Conceptual Model.* Following the overview, this chapter provides a detailed discussion of the methodology chosen to examine the process underscoring the model, and articulates the rationale in selecting the database to test the model. This chapter also examines the selection of measures for the constructs depicted in the SRID Conceptual Model.

Purpose of the Study

The purpose of this study was to investigate the various cognitive and contextual influences which may contribute to the developmental process that high school students undergo in preparing for and considering the selection of an academic major in a STEM field. This study sought to address gaps in previous research and provide a better understanding of this developmental process throughout students' high school experience, and to measure the impact self-efficacy has on students' intention to major in a STEM field. As such, this study was guided by the following research question and sub-research question:

- What are the cognitive and contextual factors impacting the developmental process high school students undergo in building readiness and intention toward a major in STEM fields of study?

    - What is the indirect effect of STEM self-efficacy on the intention to major

in a STEM field?

Conceptual Model

To address the main research question, I proposed a new conceptual model for understanding the STEM readiness and intention development process. The SRID Conceptual Model, which was introduced in Chapter 1 and described in Chapter 2, is shown in Figure 1. This model was guided by the theoretical framework of SCCT, integrating adaptations of Wang's (2013a) conceptual model of STEM choice. Building upon these foundations, the model incorporated the cognitive components of STEM self-efficacy and STEM interest, acknowledging the important role these factors have on the outcomes of STEM readiness and the intention to major in STEM. The model also included socioeconomic status (SES) and math ability as key *background characteristics* influencing this process, and incorporates parental involvement as the *contextual influence proximal to choice behavior*, which is relevant in explaining preparation for and intention to major in a STEM field of study. In summary, the SRID Conceptual Model conceptualized my hypothesis of the STEM readiness and intention development process for high school students. This model acknowledges the complex and interrelated relationships among factors throughout the developmental process through time.7

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7 SES is a key factor explaining readiness for college, and impacts math ability (Lee & Burkam, 2002; Reyes & Stanic, 1988; Sirin, 2005), parental involvement (Cabrera & LaNasa, 2000; Eagle, 1989; Leppel, Williams, & Waldauer, 2001; Ma, 2009), and STEM readiness (Hoffer, Rasinki, & Moore, 1995; Lee & Burkam, 2002; Perna, 2006). In turn, mathematical ability is known to impact STEM readiness (Hackett, 1985; Rohde & Thompson, 2007; Spinath, Spinath, Harlaar, & Plomin, 2006). Mathematical ability also impacts the extent to which a student feels self-efficacious in STEM-related content (Bandura, 1993; Bell & Kozlowski, 2002; Hackett, 1985; Pajares & Kranzler, 1995). Research also suggests that parental involvement impacts STEM self-efficacy (Alliman-Brisset, Turner, & Skovholt, 2004; Ferry, Fouad, & Smith, 2000; Turner & Lapan, 2002) and STEM readiness (Ferry, Fouad, & Smith, 2000; Mattern et al., 2015). The SCCT model suggests that self-efficacy directly impacts interest (Bandura & Schunk, 1981; Lenox & Subich, 1994; Lent et al., 1994; Rottinghaus, Larson, & Boren, 2003), which has a direct influence on intention to major in STEM (Lent et al., 2001; 2003; Natua, 2004; Scarf, 2013). The framework also supports my hypothesis that STEM self-efficacy will have a significant indirect effect on the intention to major in STEM. Research also suggests that STEM readiness, which is influenced by
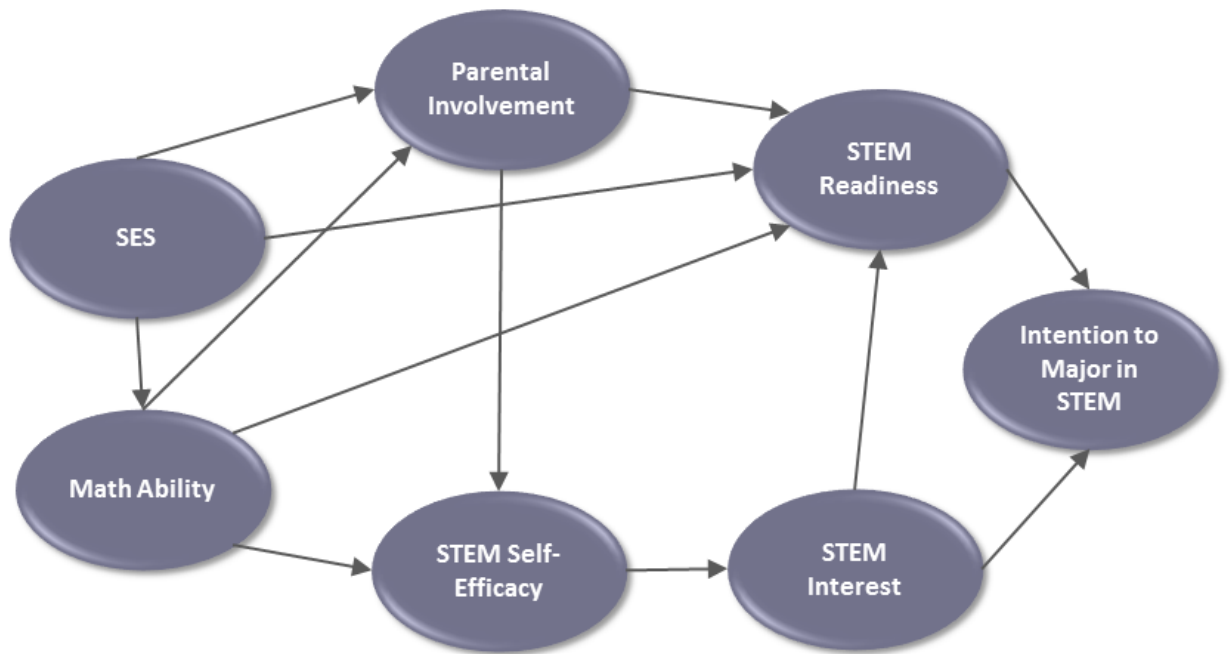
Figure 1: The STEM Readiness and Intention Development Conceptual Model

Research Design

Analytic Approach

This study was guided by the theoretical framework of the SCCT model (Lent et al., 1994). This model emphasizes the complexity of various cognitive factors and contextual influences on the STEM readiness and intention development process. Lent and associates (1994) acknowledge the interrelated and interconnected relationships as well as the complex relationships that exist among these factors throughout this process. While the majority of studies on the STEM readiness and intention development process

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STEM interest, SES, parental involvement, and math ability, directly impacts students' intention to major in STEM (Mattern et al., 2015; Sadler, Sonnert, Hazari, & Tai, 2012; Tyson, Lee, Borman, & Hanson, 2007). As such, each of the complex relationships among these various cognitive and contextual factors are illustrated in my proposed conceptual model shown below (see Figure 1).

have been limited in adopting an input-output variable approach through the use of

various forms of regression analysis (Crisp, Nora, & Taggart, 2009; Moakler & Kim,

2014; Rogers & Creed, 2011; Sax et al., 2016), I adopted an appropriate analytic

approach that reflects the complex nature of development processes, as it occurs through

time. As such, I selected structural equation modeling (SEM) as the analytic approach for

testing the model.

Unlike regression strategies, which commonly adopt an input-output variable

approach, SEM can appropriately model the complex relationships of constructs in a

process occurring through time. SEM also provides insights into measurement

characteristics and measurement error of these constructs. This approach is recognized as

a complex, multivariate statistical method that incorporates factor analysis, path analysis,

regression, and model validity techniques (Byrne, 2013; Kline, 2015). This approach

allows one to examine the complex processes taking place over time, by testing latent

constructs (e.g., cognitive concepts of self-efficacy), while modeling the relationships

among various measured factors.8 My conceptual model includes both latent and

measured constructs, which I predicted would have an impact on high school students'

intention to major in STEM.

Prior to building and testing the model with SEM, I conducted preliminary data

exploration to become familiarized with the descriptive statistics of the data and selected

variables. This step was critical in ascertaining whether there were violations of

multivariate normality in the data.9 This step also provided me with a more concrete

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8 This statistical method is commonly used in social sciences, as it allows for the imputation of
unobservable "latent" constructs, defined as using two or more observed variables (Anderson & Gerbing,
1988).
9 This is a necessary condition in multivariate statistical analysis.

understanding of the data sample from the HSLS:09 survey.

Following the preliminary data exploration, I conducted exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to test the measurement properties of the indicators I identified for each construct in the model (Brown, 2015). EFA allowed me to first explore the underlying structures of the selected variables and identify the potential relationships. Then, I conducted CFA to test the hypothesized relationships between variables and their underlying latent constructs (Suhr, 2006). CFA also allowed me to initially interpret the interconnectedness and relationships among the indicators in each construct and the extent to which the measurement model held (Brown, 2015; Hoyle, 2000). Following the testing of the measurement model, I proceeded with SEM. Effect sizes of 0.50 or greater are considered strong, effect sizes of 0.30 are moderate, and those below 0.15 are small (Pascarella & Terenzini, 2005).

Model Testing Approach

Mplus Statistical Software. I relied on Mplus statistical software (Muthén & Muthén, 2010) to conduct both the confirmatory factor analysis and the SEM components needed to test my model. In comparison to other software tools, such as LISREL or AMOS, Mplus is especially suited for taking into account complex sample designs, as followed in the High School Longitudinal Study of 2009 (HSLS:09). Furthermore, Mplus accounts for the use of both categorical and continuous variables in the analysis. As my sample incorporates both types of measures, it was necessary to use such software in my testing approach to account for the nature of categorical variables.

Sensitivity Analysis. In order to select the most appropriate analytic method within Mplus to handle missing data, it was necessary to conduct a sensitivity analysis.

The purpose of a sensitivity analysis is to explore the extent to which the results from more than one technique produce similar results (Pannell, 1997). This analysis was conducted to select the most appropriate method for handling the missing data in my dataset. I explored two estimators in the sensitivity analysis: robust maximum likelihood (MLR) and weighted least squares means and variance adjusted (WLSMV) estimator.

The MLR estimator is based on the maximum likelihood estimation for continuous variables. It is typically useful for data with non-normal distributions, as it adjusts the estimation of standard errors based on its non-normality (Kline, 2015). MLR has the advantage of being a robust estimator for missing data. However, it does not account for the use of both continuous and categorical variables, as it underestimates the relationship among variables of different types. Therefore, MLR is a method that is recommended only when the variables are continuous (Li, 2016).

The other method I tested was the WLSMV estimator. Finney and DiStefano (2006) and Mueller and Hancock (2008) recommended the use of this estimator, as it accounts for the incorporation of both categorical and continuous variable types (Finney & DiStefano, 2006; Mueller & Hancock, 2008; Muthén & Muthén, 2010). Brown (2015) describes WLSMV as a robust estimator, while also accounting for a potential lack of multivariate normality in distributions of data. The disadvantage, however, is that WLSMV uses listwise deletion to account for missing values, which excludes an entire record from analysis when a single value is missing. This technique has the potential to produce incorrect estimates, as it may reduce the sample size included in the statistical analysis and can affect the level of significance of the estimators (Olinsky, Chen, & Harlow, 2003).

The results of this sensitivity analysis are displayed below in Table 1. The sensitivity analysis revealed no statistically significant differences in the measurement or structural components of my proposed model when adapting either of the two estimators. Given that the sensitivity analysis revealed no differences in my statistical results, I opted to use the WLSMV estimator in my final SEM analyses.[10] As discussed above, unlike MLR, WLSMV accounts for the inclusion of both categorical and continuous variable types (Muthén & Muthén, 2010). As my dissertation dataset includes both categorical and continuous variables, the WLSMV technique is the estimator most closely aligned with the nature of my data. However, the sensitivity analysis suggests that either estimator could be used.

Table 1: Sensitivity Analysis

	WLSMV	MLR
PARENT BY		
P2COURSE	0.693	0.629
P2CLGEXM	0.882	0.783
P2CLGAPP	0.836	0.794
P2CAREER	0.781	0.668
READY BY		
MATHCRED	0.555	0.685
SCICRED	0.664	0.769
GPASTEM	0.840	0.692
MATHEFF BY		

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[10] My decision to select WLSMV, confirmed by the results of my sensitivity analysis, is consistent with the comparative performance analysis performed by Li (2016). When comparing the performance of MLR and WLSMV, Li (2016) found that in general, factor loadings from WLSMV were more precise and accurate in comparison to those obtained by MLR, especially when there was a moderate violation of latent normality.

MESKILL	0.896	0.818
METEST	0.911	0.842
METEXT	0.848	0.757
MEEXCL	0.928	0.851
SCIEFF BY		
SESKILL	0.893	0.802
SETEST	0.874	0.803
SETEXT	0.833	0.734
SEEXCL	0.890	0.816
SES BY		
INCOME	0.717	0.719
MOED	0.774	0.713
FAED	0.810	0.759
PARENT ON		
SES	0.408	0.401
MATHEFF ON		
PARENT	0.064	0.067
SCIEFF ON		
PARENT	0.130	0.141
READY ON		
PARENT	0.190	0.225
SES	0.200	0.188
PARENT ON		
X1TXMTH	0.130	0.113
MATHEFF ON		
X1TXMTH	0.307	0.302
SCIEFF ON		

X1TXMTH	0.219	0.196
READY ON		
X1TXMTH	0.408	0.335
X1MTHINT	0.186	0.130
X1SCIINT	0.081	0.049
X1TXMTH ON		
SES	0.413	0.462
X1MTHINT ON		
MATHEFF	0.552	0.549
X1SCIINT ON		
SCIEFF	0.521	0.524
MJRSTEM ON		
READY	0.361	0.302
MJRSTEM ON		
X1MTHINT	0.101	0.049
X1SCIINT	0.199	0.066
MATHEFF WITH		
SCIEFF	0.419	0.394
Note: All values are statistically significant p<0.005.		

Indirect Effects. To answer the secondary research question, I relied on testing for the indirect effect of self-efficacy on the intention to major in a STEM field (Byrne, 2013). Indirect effects testing facilitated the estimation of the direct, indirect, and total effects exhibited by STEM self-efficacy through STEM interest. Testing for this indirect effect was the last step in my model testing approach.

Model Fit Indices. To evaluate goodness of fit, I relied on several model fit

indices. These indices included the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and chi-square estimation. The CFI and TLI were used to estimate the extent to which the model provided an appropriate fit to the data (Brown, 2015). CFI and TLI values greater than 0.95 are indicative of a strong model fit (Brown, 2015). Similarly, the RMSEA index evaluates fit, while also accounting for the large sample size used. RMSEA values between 0.00 and 0.05 indicate good fit, while values greater than 0.10 suggest a poor fit (Byrne, 2013; Hu & Bentler, 1999). When referring to confidence intervals, I estimated at 90% confidence, rejecting the model if the RMSEA value was at or under 0.10 (Brown, 2015; Byrne, 2013).

Reliability. To appraise the reliability of the items underlying each of the latent constructs, I relied on Raykov's (2009) composite of reliability ω. Though widely used, Cronbach's alpha is a less dependable indicator for the internal consistency of scales, as it incorrectly assumes that the items are measured without error. Furthermore, coefficient alpha presumes that each item has a similar loading in the construct. Rather than using coefficient alpha, I assessed reliability using composite reliability ω, which assumes that the strength of the association will vary across items and that the items are measured with some level of error (Raykov, 2009; Stapleton, Yang, & Hancock, 2016).

Data Source

This dissertation study relied on data from HSLS:09. HSLS:09 is a national longitudinal database administered by the United States Department of Education's National Center for Education Statistics (NCES) following a cohort of 9th grade students beginning in 2009 through the most recent follow-up of data gathered in spring 2013

when the students were in their expected graduation year of high school.[11]

I selected HSLS:09 for my dissertation study for several reasons. First, previous research (Lent et al., 2003; 2008a; 2008b) has emphasized the importance of using longitudinal data when examining the career development process outlined in SCCT. In this regard, HSLS:09 is ideally suited to explore the process of preparing for and considering the selection of a STEM major throughout high school. Using HSLS:09 longitudinal data, I examined factors influencing STEM readiness and intention development from the time students were in their first year of high school and their subsequent behaviors, actions, and intentions throughout their high school career. Moreover, HSLS:09 is the most recent nationally representative longitudinal database available, providing data following the most recently surveyed cohort of high school students from 9th grade in 2009 with continued data collection through 2021.[12]

Second, unlike the previous national longitudinal database (i.e., Educational Longitudinal Study of 2002) HSLS:09 survey design includes numerous measures directly related to STEM.[13] This allowed me to use a more precise measure of student academic performance in and exposure to STEM-related content, as well as a more nuanced understanding of self-efficacy and interest in STEM-related fields.

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[11] In the base year of 2009, approximately 23,000 9th graders were surveyed, along with their parents, counselors, and school administrators, from 944 schools. The first follow up occurred in 2012, when the students were in 11th grade, and the second follow-up occurred in 2013, when the students were projected to have graduated from high school. High school transcript data was also collected from 2013 to 2014.

[12] This longitudinal survey continues through students' postsecondary education, and the second follow-up of data collection is currently in collection by NCES through 2017.

[13] HSLS:09 includes newer measures for the 2009 cohort focusing on the current national and educational context. HSLS:09 focuses on students' trajectories and aspirations for postsecondary education and the workforce, as well as the selection process of STEM courses, majors, and careers (Ingels et al., 2011). Given the importance of national focus on improving enrollment in and graduation from STEM fields (Committee on STEM, 2013; National Science Board, 2015), HSLS:09 includes numerous measures and items related to science, technology, and math, in an effort to better capture the student experience in relation to STEM-relevant content and the desire to pursue STEM-related majors and careers.

Third, given that HSLS:09's survey design includes measures from students and their parents, my study included self-reported measures from students' parents on the extent to which they were involved in their child's schooling during the secondary educational period. Furthermore, many of these measures of data are corroborated with non-self-reported data, including high school transcripts, College Board, Common Core, and the Integrated Postsecondary Education Data System data (Ingels et al., 2015).

Accounting for Sampling Design Effects

HSLS:09 follows a complex, multi-stage sample strategy with unequal probability of sample selection, to represent the population of 9th grade students in 2002 (Ingels et al., 2014). Stapleton (2013) notes that both confirmatory factor analyses and SEM are prone to produce biased point estimates and large sampling variances when using complex sample designs, as those incorporated in HSLS:09.[14] Accordingly, I relied on the *pseudomaximum likelihood estimation method* in Mplus, which accounts for the incorporation of the primary sampling unit (PSU) for clustering, the stratum ID (STRAT_ID) for sample stratification, and the weighting variable (W3W1W2STU) for estimation of the national population. The selected panel weight allowed me to include only those 9th grade students who participated in the base year (2009), in the first follow-up (2012), and when the students were in 12th grade (2013). According to Ingels and associates (2015), the W3W1W2STU weighting variable appropriately accounts for missing cases in which students did not participate in one or more of the follow-up NCES surveys.

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[14] In addition, large sampling variances can occur when using structural modeling with a complex sampling design, which can increase the likelihood of a making a type-1 error (Heck & Thomas, 2015).

Constructs and Measures

The proposed conceptual model was comprised of five latent constructs and two

single variables, including the outcome variable for the intention to select a STEM major.

The latent constructs include SES, Parental Involvement, STEM Self-Efficacy, STEM

Interest, and STEM Readiness.[15] The two single variables include math ability and the

intention to major in a STEM field. Table 2 provides a summary of the constructs and

their corresponding indicators and the single variable measures. In this section, I also

provide definitions of the constructs and the rationale for the selection of their

corresponding measures.

Table 2: Constructs and Indicators

Construct	Concept	Indicators
SES	Indicator of wealth/ socioeconomic status	• Family income (X1FAMINCOME) • Mother's education (X1MOMEDU) • Father's education (X1DADEDU)
Math Ability	Intellectual/academic ability in math	• Student's ability level in math (in 9th grade) (X1TXMTH)
Parental Involvement	Parent involvement in student's academics, schooling, career, and future plans	• How often discussed courses or programs at school (P2COURSE) • How often discussed careers he/she may be interested in (P2CAREER) • How often discussed preparing for college entrance exams (P2CLGEXM) • How often discussed applying to

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[15] In Chapters 3, 4, and 5, *constructs* will be designated by the capitalization of these factors, while the *concepts* will be designated by non-capitalization of these factors (e.g. Parental Involvement (construct) vs. parental involvement (concept)).

		• college/other schools after high school (P2CLGAPP) • Has arranged for student to attend college tour or campus program (P2CLGTOUR)
STEM Self-efficacy	Self-efficacy in math and science	• Confidence in math tests (S1MTESTS) • Confidence in science tests (S1STESTS) • Certainty in understanding math textbook (S1MTEXTBOOK) • Certainty in understanding science textbook (S1STEXTBOOK) • Certainty in mastering skills in math (S1MSKILLS) • Certainty in mastering skills in science (S1SSKILLS) • Confidence in excelling in math assignments (S1MASSEXCL) • Confidence in excelling science assignments (S1SASSEXCL)
STEM Interest	Interest in math and science	• Scale of student's interest in math (in 9th grade) (X1MTHINT) • Scale of student's interest in science (in 9th grade) (X1SCIINT)
STEM Readiness	Academic achievement in and exposure to STEM-related courses	• GPA in all STEM courses (X3TGPASTEM) • Credits earned in math courses (X3TCREDMAT) • Credits earned in science courses (X3CREDSCI)
Intention to Major in STEM (outcome variable)	Intention to select STEM major	• Major student considering in postsecondary education (by 12th grade) (X3FIELD_STEM)

Socioeconomic Status

SES is a measure of economic and sociological standing in society, commonly

measured by combinations of income, occupation, or education (Cowan et al., 2012). The

construct of SES was appraised by measures of both familial wealth and parental

education, including mother's (or female guardian's) education (X1MOMEDU) and

father's (or male guardian's) education (X1DADEDU), along with family income

(X1FAMINCOME). These measures reflect the social, economic, cultural, and

environmental conditions to which students are exposed. These items were collected

during the base year (2009) of the survey from the parent respondents. Due to the

skewness of the family income variable, I recoded the variable to more closely reflect a

normal distribution of data. The variable X1FAMINCOME was recoded into a variable

with seven categories: 1: "Less than $15,000;" 2: "$15,000-$35,000;" 3: "$35,000-

$55,000;" 4: "$55,000-$95,000;" 5: "$95,000-$135,000;" 6: "$135,000-$195,000;" and 7:

"$195,000+."

Math Ability

Math ability impacts the extent to which students meet benchmarks in becoming

academically prepared for a STEM field of study (Hackett, 1985; Rohde & Thompson,

2007; Spinath, Spinath, Harlaar, & Plomin, 2006). To appraise the construct of Math

Ability, I relied on a single item score (X1TXMTH) from HSLS:09's math assessment[16]

of algebraic reasoning and ability in math.[17] This math ability test was administered to all

participants in the base year (2009) of the HSLS:09 survey, when the students were in the

9th grade (Ingels et al., 2011).

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[16] The framework for this assessment was "developed by the staff at the American Institutes of Research
with support of and review by John Dossey, Professor Emeritus of Mathematics at Illinois State University,
who served as a project consultant" (Ingels et al., 2011, p. 23).

[17] This continuous variable is a theta score, which provides an estimate of ability and achievement of 9th
grader in comparison to the estimated population as a whole.

Parental Involvement

       Parental involvement can be defined as the extent to which a parent is involved in a child's academic and schooling experience, which has been strongly related to students' overall educational experience and academic achievement and subsequent college enrollment (Cabrera & LaNasa, 2000; Fan & Chen, 2001; Jeynes, 2007; McNeal, 1999; Perna & Titus, 2005; Reynolds, 1992). Cabrera and LaNasa (2000) suggest that parental involvement can be measured by both motivational and behavioral dimensions. The proactive and interactive behaviors of parents can have a stronger impact on high school students' academic achievement (Stewart, 2008) and college enrollment (Perna & Titus, 2005). According to Hill and Tyson (2009), parental involvement behaviors that reflect academic socialization have the strongest impact on students' achievement. Academic socialization behaviors include communication about parental expectations for education, discussing school work and activities, and discussing plans and preparations for the future (Hill & Tyson, 2009).

       Accordingly, I appraised the construct of parental involvement via five indicators of proactive parental involvement in students' schooling, as well as academic and career development. These item responses were collected in the first follow-up administered in 2011 from the parent survey, while the cohort of students was in the 11th grade. These indicators include: (1) "How often discussed courses or programs at school" (P2COURSE); (2) "How often discussed careers he/she may be interested in" (P2CAREER); (3) "How often discussed preparing for college entrance exams" (P2CLGEXM); (4) "How often discussed applying to college/other schools after high school" (P2CLGAPP); and (5) "Has arranged for student to attend college tour or campus

program" (P2CLGTOUR). The response options for the first four variables include four categories: 1: "Never;" 2: "Once or twice;" 3: "Three or four times;" and 4: "More than four times." The response options for P2CLGTOUR are "Yes" or "No."

STEM Self-Efficacy

Self-efficacy can be defined as one's belief in his or her ability to succeed in accomplishing a task. Self-efficacy is often interpreted as one's mastery of experiences and skills, and confidence in one's ability to perform and succeed (Bandura, 1977). Aligned with Bandura's (2006) guide for constructing self-efficacy scales, I approached STEM self-efficacy as one's belief in a mastery of skills and confidence in performance in the domains of STEM-relevant content, including math and science. Accordingly, I appraised the latent construct of STEM self-efficacy by four HSLS:09 items in both math and science self-efficacy.[18] These items include: (1) "9th grader confident can do excellent job on math/science tests" (S1MTESTS, S1STESTS); (2) "9th grader certain can understand math/science textbooks" (S1MTEXTBOOK, S1STEXTBOOK); (3) "9th grader certain can master skills in math/science" (S1MSKILLS, S1SSKILLS); and (4) "9th grader confident can do excellent job on math/science assignments" (S1MASSEXCL, S1SASSEXCL) (Ingels et al., 2011, p. 109). Each of these raw variables includes four response values: (1) "Strongly Agree; (2) "Agree;" (3) "Disagree;" and (4) "Strongly Disagree." To adjust for the skewness in each variable (i.e., respondents were less likely to select "Strongly Disagree" or "Disagree" on the Agree-Disagree scale), I recoded each self-efficacy variable into three categories

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[18] Selection of these items was guided by the NCES's development of the scaled scores for student variables, as determined by principle component factor analysis, with reliability assessed using Cronbach's alpha (Ingels et al., 2011).

(combining responses for "Disagree" and "Strongly Disagree") and reverse coded them to reflect a positive direction.

STEM Interest

STEM interest can be defined as one's interest in the fields of science, technology, engineering, or math. More specifically in high school, where core academic courses in STEM domains are focused on math or science, STEM interest can be understood as high school students' interest in math or science classes, course content, or careers in STEM fields (Sadler et al., 2012; Seymour & Hewitt, 1997; Tyler-Wood, Knezek, & Christensen, 2010). In appraising STEM interest, I relied on two continuous variables created by NCES,[19] measuring interest in math and interest in science (X1MTHINT, X1SCIINT). NCES analysts created these scales through principal components factor analysis, using the following six HSLS:09 items: (1) "9th grader is taking math/science because he/she really enjoys math/science;" (2) "9th grader thinks math/science is a waste of time;" (3) "9th grader thinks math/science is boring;" (4) "Favorite subject is math/science;" (5) "Least favorite subject is math/science;" and (6) "9th grader is enjoying math/science course very much" (Ingels et al., 2011, p. 109). These two scales capture whether or not the students are interested in and enjoy their math and science courses, and whether or not they find the course content to be useful to them.

STEM Readiness

STEM readiness refers to the extent to which a high school student is

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[19] According to Ingels et al. (2011), the questionnaires were cleaned and reverse coded and the reliability of the scale items were assessed using Cronbach's alpha, which measures how closely related a set of items are as a group in a survey instrument (Santos, 1999).

academically and experientially prepared to pursue a STEM field of study (Mattern,

Radunzel, & Westrick, 2015). The 2015 ACT report emphasizes that STEM readiness is

more specific than college readiness, in that it focuses on achievement in the academic

domains of math, science, and other STEM-related content. Specific benchmarks for

STEM readiness, which extend beyond benchmarks for college readiness, have been

proposed (Mattern et al., 2015). Since STEM fields of study often demand a strong

knowledge base, skills, and abilities in the domains of math and science (Chen, 2009;

Crisp et al., 2009; Whalen & Shelley, 2010), STEM readiness benchmarks revolve

around achievement in these subjects. More specifically, STEM readiness can be

benchmarked through both academic performance and credits earned in math and science

(Chen, 2013; Maltese & Tai, 2011; Mattern et al., 2015; Thompson & Bolin, 2011; Tyson

et al., 2007). As supported by this literature, I selected three indicators from HSLS:09 to

appraise the construct of STEM readiness: (1) GPA in all STEM courses

(X3TGPASTEM); (2) Credits earned in math courses[20] (X3TCREDMAT); and (3)

Credits earned in science courses[21] (X3TCREDSCI)." To adjust for skewness, I recoded

the GPA variable into seven categories: 1: "Up to 1.0;" 2: "Up to 1.5;" 3: "Up to 2.0;" 4:

"Up to 2.5;" 5: "Up to 3.0;" 6: "Up to 3.5;" and 7: "Up to 4.0." I also recoded the raw

math and science credit variables to adjust for skewness, and to have consistent

categories. Both the math and science credits variables were recoded into six categories:

1: "Fewer than 1;" 2: "1-2 credits;" 3: "2-3 credits;" 4: "3-4 credits;" 5: 5-6 credits;" and

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[20] Math courses include basic math, pre-algebra, algebra I, geometry, algebra II, trigonometry, probability and statistics, AP/IB math, pre-calculus, calculus, AP/IB calculus, other basic math, and other advanced math.
[21] Science courses include general science, specialty science, advanced studies in science, and AP/IB science.

6: "More than 6 credits."

Intention to Major in STEM

The variable I selected from the HSLS:09 database is a measurement of the 12th grader's intention to major in a STEM field.[22] This variable for STEM major selection was transformed by NCES based on the original question: "What field of study or program [will/were/was] [you/he/she] [be] considering?" (Ingels et al., 2015). This variable captures 12th graders' responses regarding whether they are considering majoring in a STEM field, namely in science, technology, engineering, or math.[23] The raw variable (S3FIELD_STEM) included three response categories: (1) "No (not in STEM);" (2) "Yes (in STEM);" and (3) "Don't Know." To eliminate ambiguity and assess certainty in students' intention to major in STEM, I recoded this variable to combine the "No" and "Don't Know" categories. This provides me with a binary variable for the major the student is intending to select: "Not in STEM" and "Yes in STEM."

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Chapter Summary

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This chapter provided an in-depth overview of the methodology for my dissertation study. After reviewing my conceptual model of the STEM readiness and intention development process, I described the research design selected for analyzing the data. As discussed, I first conducted preliminary analyses on the dataset to explore the descriptive statistics of the data composition and the selected variables, checking for multivariate normality. Next, I conducted EFA and CFA to test the measurement model

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[22] As actual selection of major has not yet been captured in the most recent follow-up of the HSLS:09 survey, intention to major is the best measure available for a student's selection of major.
[23] NCES considers the following majors in their categorization of STEM: Computer and Information Science and Support Services, Engineering, Engineering Technologies/Technicians, Biological and Biomedical Science, Mathematics and Statistics, Physical Sciences.

for each construct and determined whether the hypothesized indicators selected were

consistent with the underlying nature of that construct. In order to select the most

appropriate analytic method to account for missing data, I performed a sensitivity

analysis, which revealed no differences in the results between the use of the two

estimators, MLR and WLSMV. Finally, I proceeded with SEM analyses using Mplus to

test the structural paths and model that I propose. The study relied on data from HSLS:09

to appraise the constructs of SES, Math Ability, Parental Involvement, STEM Self-

Efficacy, STEM Interest, STEM Readiness, and Intention to Major in STEM.

Chapter IV: Results

This chapter presents the findings from my dissertation study, which was guided by the following research question and sub research question:

- What are the cognitive and contextual factors impacting the developmental process high school students undergo in building readiness and intention toward a major in STEM fields of study?
  - What is the indirect effect of STEM self-efficacy on the intention to major in a STEM field?

As explained in Chapter 3, answering these two research questions calls for testing of the measurement and structural components of the *STEM Readiness and Intention Development (SRID) Conceptual Model* I proposed in Chapter 2. This model illustrates the various factors, both cognitive and contextual, influencing high school students' development in relation to preparing for and intending to major in a STEM field. This model builds upon SCCT and Wang's (2013) model of STEM choice, incorporating important constructs and measurements omitted by the extant literature (including parental involvement), while also including self-efficacy and interest in STEM-related content as key cognitive components in the developmental process. Accordingly, my model presumes that background characteristics are represented by socioeconomic status (SES) (*background contextual affordance*), which include parental education and family income, as well as math ability (*personal input characteristics*). As an interpretation of SCCT's *contextual influence proximal to choice behavior*, the SRID Conceptual Model highlights parental involvement as a key factor influencing the preparation for and intention to major in a STEM field.

This chapter begins by providing a profile of the national cohort of high school students who were first surveyed as 9th grade students in 2009, and followed through their senior year of high school, at the moment many students were making important decisions about their future educational plans and careers. The purpose of the first section is to begin by providing a general profile of this nationally representative sample of students, highlighting the differences among those who considered pursuing STEM in comparison to those who did not. Next, I discuss the findings from the exploratory factor analysis (EFA) on the variables to explore the extent to which the items group with the constructs of my proposed model. Finally, I discuss the results from the confirmatory factor analysis (CFA) (measurement model results) and the structural equation model (SEM) analysis (structural model results).

Descriptive Analysis

Sample Profile

Prior to presenting the findings from the analyses, I offer an overview of the 2009 cohort of 9th grade students in view of the constructs and indicators in the SRID Conceptual Model. Accordingly, Table 3 presents the descriptive statistics[24] of the 2009 cohort, including means, standard deviations, minimums, maximums, and the percentage of data missing for each variable included in the study's analyses. Table 3 also presents the results from the normality tests, including the Doornik-Hansen multivariate test and the Mardia tests for skewness (measure of symmetry) and kurtosis (measure of

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[24] As this study uses restricted data from the IES National Center for Education Statistics, the descriptive statistics I present comply with the policies of IES to report rounded means and standard deviations to one decimal place.

"tailedness"), which were used to determine if the data models had a normal distribution. These tests (see last row in Table 3) revealed that there is a lack of normality in the data, which called for the use of using advanced techniques of weighted least squares means and variance adjusted (WLSMV) estimator or robust maximum likelihood (MLR) with the structural equation modeling (SEM) analyses, as discussed in Chapter 3.[25]

Table 4 presents a comparison of each of the proposed variables with the main outcome variable of interest: Intention to Major in a STEM field. This variable captures 12th grade students' responses regarding whether they are considering to major in a STEM field, namely in science, technology, engineering, or math. The descriptive analysis revealed that almost a quarter (23.3%) of the 12th grade students intended to major in STEM. To compare differences between the two sample populations (i.e., those who intended to major in STEM and those who did not), I conducted a test for difference in means.[26] As cross-tabulation analysis is a more appropriate method for comparing categorical variables, I compared the categorical variables of interest with the Intention to Major in STEM variable using cross tabulation. I also reported Pearson's chi-square and Cramer's V to assess the strength of the association between the variables, and determine whether the associations are statistically significant. Pearson's chi-square test evaluates the likelihood of difference between the two groups, and Cramer's V measures the association between the two variables (varying from 0 to 1). These results are reported together in Table 4.

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[25] See Chapter 3 for details on the sensitivity analysis and subsequent selection of the WLSMV method of SEM, which accounts for a lack of normality in the data.

[26] Note: The negative values displayed in the mean difference and t-statistic column indicate the negative relationship among students who did not intend to major in a STEM field as the variables of interest. This negative association suggests descriptive differences in these items, in comparison to those who intend to major in STEM.

Demographic overview. The 2009 sample of 9th grade students is comprised of 53.1% women and 46.9% men. In terms of racial/ethnic demographics, the 2009 cohort was 56.5% White, 9.9% Black and African American, 14.2% Hispanic, 10.5% Asian, 8.1% multi-racial, and about 0.8% Native American or other. Among those who considered pursuing a STEM major, 34.6% were women and 65.4% were men. The racial/ethnic demographic of the students who considered a major in a STEM field is comprised of 55.6% White, 6.7% Black and African American, 11.5% Hispanic, 17.5% Asian, 7.6% multi-racial, and about 1.1% Native American or other.

Math Ability

The math ability item (X1TXMTH) is a continuous variable ranging from -2.58 to 3.03 (see Table 3). The mean is 0.0, which falls just below the median, and the standard deviation is 1.0. All students in the 2009 cohort were assessed on math ability in the 9th grade. Twelfth grade students reporting their intention to major in STEM had a mean score of 0.76, while those who did not had a mean score of 0.19. This suggests that students with stronger math ability were more likely to consider majoring in a STEM field of study ($t=29.40, p<0.00$).

Socioeconomic Status

The SES construct is comprised of three variables: family income (X1FAMINCOME), mother's education (X1MOMEDU), and father's education (X1DADEDU). The 2009 cohort of 9th grade students had a mean family income of 3.7 on a 1 to 7 scale (see Table 3), which reflected an average family income of approximately $55,000 to $95,000 per year. The average level of education for both parents among the 9th grade cohort was the completion of an Associate's degree.

When comparing the SES of those students who intended to major in STEM and those who did not, there were only slight differences in family income, mother's education, and father's education. As displayed in Table 4, there are statistically significant differences in family income and parental education, suggesting that those students who did not intend to major in STEM have slightly lower family income, mother's education, and father's education.

Parental Involvement

Five indicators were selected for the construct of Parental Involvement: parental discussions of school courses (P2COURSE), college entrance exams (P2CLGEXM), applying to college (P2CLGAPP), careers of interest (P2CAREER), and whether the parent arranged for a college tour (P2CLGTOUR). Most of the indicators of parental involvement, with the exception of P2CLGTOUR, displayed means between 3.0 and 3.5 in a scale ranging from 1 to 4 (see Table 3). In other words, most parents discussed topics, such as school courses, future careers, applying to college, and college entrance exams, with their students an average of three to four times by the time students reached the 11th grade. In regards to P2CLGTOUR about half of the 2009 cohort had parents who arranged a college tour or campus program.

Significant, but relatively small, differences were identified when comparing those students who intended to major in STEM and those who did not with regards to parental involvement. Those students who indicated intent to major in STEM received greater levels of parental involvement. As displayed in Table 4, there were significant differences between how often parents discussed school courses, college entrance exams, applying to college, and arranging for college tours. However, no significant differences

were found in how often parents discussed careers in which the student may be interested. Table 4 displays the chi-square and Cramer's V, assessing the magnitude and association of the observed differences.

STEM Self-Efficacy

There are eight total self-efficacy indicators, four in the math domain (S1MTESTS, S1MTEXTBOOK, S1MSKILLS, S1MASSEXCL) and four in the science domain (S1STESTS, S1STEXTBOOK, S1SSKILLS, S1SASSEXCL). All self-efficacy variables ranged from 1 to 3, with means ranging from 1.7 (S1STEXTBOOK) to 2.1 (S1MASSEXCL) (see Table 3). Such high means indicates that on average, the 2009 cohort of 9th grade students responded that they "Agree" that they are confident or certain in various areas of both math and science domains.

As shown in Table 3, there were significant differences among all self-efficacy variables between those students in the 2009 cohort who intended to major in STEM and those who did not. Those students who reported intent to major in STEM also reported higher levels of self-efficacy in 9th grade. The associated significant differences between these two groups were substantial (see chi-square values and Cramer's V in Table 4), indicating that there are observed differences in self-efficacy measures between those students in the 2009 cohort who intended to major in STEM and those who did not intend to major in STEM.

STEM Interest

For the construct of STEM Interest, I selected two continuous scaled variables, X1MTHINT and X1SCIINT, appraising interest in math and science respectively. With means of 0 and standard deviations of 1.0, these variables ranged from approximately -

2.5 to approximately 2.05, indicating a normal (slightly skewed to the right) distribution of scores among the 2009 cohort of 9th grade students (see Table 3).

When comparing the mean differences between those students who intended to major in STEM and those who did not, I found statistically significant differences for students' interest in math ($t=12.52, p<0.00$) and students' interest in science ($t=13.85, p<0.00$) (see Table 4). This suggests that students intending to major in STEM displayed higher levels of interest in math and science in 9th grade in comparison to those who did not intend to major in STEM.

STEM Readiness

The variables I selected for the STEM Readiness construct included the credits earned in math courses (X3TCREDMAT), credits earned in science courses (X3TCREDSCI), and grade point average (GPA) in all STEM courses (X3TGPASTEM). The variables for credits earned in math and credits earned in science both range from 0 to 6, with means of 3.5 and 3.1 respectively (see Table 3). This indicates that on average, by the time students were in 12th grade, they earned two to four credits in math courses, and two to three credits in science courses. GPA in STEM courses ranged from 1 to 7, with a mean of 4.3 indicating an average GPA in STEM courses of up to 2.5.

In comparing STEM readiness between those students who reported an intention to major in STEM, I found that students who intended to major in STEM earned more credits in math courses ($t=13.44, p<0.00$), and science courses ($t=25.22, p<0.00$). They also had a higher GPA in STEM courses ($t=25.56, p<0.00$). This implies differences among the extent to which these two groups of students in the 2009 cohort prepared themselves for study in a STEM field –particularly through their course taking patterns

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and academic performance in STEM courses – with students intending to major in STEM

earning more credits in math and science courses, as well as earning a higher GPA in

STEM courses.

[Table 3 and Table 4 on next pages]

Table 3: Descriptive statistics

Construct/Variable	Mean	Std. Dev.	Min	Max	% Missing
Math Ability					
Ability level in math (X1TXMTH)	0.0	1.0	-2.58	3.03	0.00
Socioeconomic Status					
Family income (recode of X1FAMINCOME)	3.7	1.7	1	7	0.18
Mother's education (recode of X1MOMEDU)	3.0	1.3	1	7	0.04
Father's education (recode of X1DADEDU)	3.1	1.6	1	7	0.02
Parental Involvement					
Parent discussion on school or selecting courses (P2COURSE)	3.1	0.9	1	4	0.84
Parent discussion on preparing for college entrance exams (P2CLGEXM)	3.0	1.1	1	4	1.17
Parent discussion on applying to college or other school (P2CLGAPP)	3.2	1.0	1	4	1.17
Parent discussion on careers of interest (P2CAREER)	3.5	0.8	1	4	1.11
Parent has arranged for student to attend college tour or campus program (P2CLGTOUR)	0.5	0.5	0	1	0.39
STEM-Self Efficacy					
Confidence in math tests (recode of S1MTESTS)	2.0	0.7	1	3	1.46
Certainty in understanding math textbook (recode of S1MTEXTBOOK)	1.8	0.7	1	3	1.68
Certainty in mastering skills in math (recode of S1MSKILLS)	2.0	0.7	1	3	1.84

Confidence in excelling in math assignments (recode of S1MASSEXCL)	2.1	0.7	1	3	2.10
Confidence in science tests (recode of S1STESTS)	1.9	0.7	1	3	1.73
Certainty in understanding science textbook (recode of S1STEXTBOOK)	1.7	0.7	1	3	1.89
Certainty in mastering skills in science (recode of S1SSKILLS)	1.9	0.7	1	3	2.09
Confidence in excelling in science assignments (recode of S1SASSEXCL)	2.0	0.6	1	3	2.36
STEM Interest					
Scaled interest in math (X1MTHINT)	0.0	1.0	-2.46	2.08	3.72
Scaled interest in science (X1SCIINT)	0.0	1.0	-2.59	2.03	3.59
STEM Readiness					
Credits earned in math (recode of X3TCREDMAT)	3.5	1.3	0	6	6.25
Credits earned in science (recode of X3TCREDSCI)	3.1	1.3	0	6	6.25
GPA in all STEM courses (recode of X3TGPASTEM)	4.3	1.8	1	7	0.17
Intention to Major in STEM					
STEM major consideration (recode of S3FIELD_STEM)	0.2	0.4	0	1	1.68

Multivariate Normality Tests	Doornik-Hansen multivariate test = 10,101.6, $p<0.001$
	Mardia multivariate skewness = 20.1, $p<0.001$
	Mardia multivariate kurtosis = 601.7, $p<0.001$

Table 4: Descriptive Comparison Analysis

Comparing association with Intention to Major in STEM variable	Pearson X^2	Cramer's V
Socioeconomic Status		
Family income (X1FAMINCOME)	99.06***	0.0974
Mother's education (X1MOMEDU)	149.86***	0.1227
Father's education (X1DADEDU)	147.57***	0.1312
Parental Involvement		
How often discussed courses or programs at school (P2COURSE)	11.55**	0.0479
How often discussed careers he/she may be interested in (P2CAREER)	4.09	0.0285
How often discussed preparing for college entrance exams (P2CLGEXM)	36.13***	0.0847
How often discussed applying to college/other schools after high school (P2CLGAPP)	25.68***	0.0714
Has arranged for student to attend college tour or campus program (P2CLGTOUR)	12.79***	0.0504
Math Self-Efficacy		
Confidence in math tests (S1MTESTS)	249.24***	0.1515
Certainty in understanding math textbook (S1MTEXTBOOK)	291.43***	0.1640
Certainty in mastering skills in math (S1MSKILLS)	286.37***	0.1627

Confidence in excelling in math assignments (S1MASSEXCL)	225.23***	0.1444

Science Self-Efficacy		
Confidence in science tests (S1STESTS)	296.77***	0.1712
Certainty in understanding science textbook (S1STEXTBOOK)	283.98***	0.1675
Certainty in mastering skills in science (S1SSKILLS)	273.67***	0.1646
Confidence in excelling science assignments (S1SASSEXCL)	223.17***	0.1488

Difference of means testing (for continuous variables)	Mean difference	*t*-statistic
Math Ability		
Math Ability (X1TXMTH)	0.57	29.40***
STEM Interest		
Math Interest (X1MTHINT)	0.28	12.52***
Science Interest (X1SCIINT)	0.32	13.85***
STEM Readiness		
Credits earned in math (X3TCREDMAT)	0.29	13.44***
Credits earned in science (X3TCREDSCI)	0.61	25.22***
GPA in all STEM courses (X3TGPASTEM)	0.78	25.56***

Significance level: p<0.10, p< 0.05** p<0.01 ****

Conclusions from Descriptive Analysis

The profile derived from this descriptive analysis suggests that students who intended to major in STEM, in comparison to those who did not, had parents who were involved in students' educational experiences, particularly in discussing school courses and strategies for preparing for college. Furthermore, students who intended to major in STEM exhibited higher levels of math ability in the 9th grade, as well as higher self-efficacy measures in math and science domains and greater interest in math and science. By the 12th grade, students intending to major in STEM earned more credits in math and science and a higher GPA in STEM courses in comparison to their counterparts.

While the descriptive analyses provide a basic understanding of the composition of the data sample, as well as comparisons of differences between students who are and are not considering a STEM major, these results are merely descriptive. These analyses do not take into account the complex relationships among various influential factors throughout high school. The subsequent analyses of this study build upon the descriptive findings, acknowledging the complexity and nuances of the latent and non-latent cognitive and contextual constructs influencing STEM readiness and intention development.

The next sections describe the two stages of analyses. The first stage describes the examination of the measurement properties of the 21 indicators presumed to reflect the constructs of my conceptual model. The analyses in this first stage consist of EFA, followed by CFA. The second stage of analysis focuses on addressing the study's research questions through SEM and indirect effect testing.

Exploratory Factor Analysis Results

I conducted an EFA on 21 of the 23 items[27] listed in Table 3. Specifically, I sought to explore the extent to which the items I selected for each construct grouped in a manner consistent with my conceptual model (see Figure 1). The results of the EFA include estimates, referred to as factor loadings (Fabrigar & Wegener, 2011), of both the strength and the direction of the common factors for each of the examined measures. EFA also produces estimates of the number of factors that best account for the correlations among the items. This analysis helped me to identify whether the items I selected could be considered as a reliable measure of the intended construct. Following recommendations from the SEM literature (e.g., Brown, 2015; Kline, 2005), I regarded items with loadings greater than 0.5 to be a reliable indicator of the corresponding construct.

The EFA yielded a five-factor solution accounting for 17% of the variance observed in the correlation matrix. Table 5 reports the loadings for each of the 20 items in the five factors, as well as the variance explained by each of the five factors (see last row in Table 5).

[Table 5 on next page]

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[27] Two items were not included in the EFA: math ability (X1TXMTH) and Intention to major in STEM (S3FIELD_STEM). These variables were not included because they each represent the only indicator in a single non-latent construct.

Table 5: Exploratory Factor Analyses

Item	Socioeconomic Status	Parental Involvement	Math Self-Efficacy	Science Self-Efficacy	STEM Readiness
Family income (X1FAMINCOME)	**0.782**	-0.009	-0.045	-0.005	-0.052
Mother's education (X1MOMEDU)	**0.796**	0.029	-0.033	0.011	-0.057
Father's education (X1DADEDU)	**0.821**	-0.027	-0.024	-0.018	0.001
How often discussed courses or programs at school (P2COURSE)	-0.63	**0.752**	0.038	0.012	-0.073
How often discussed careers he/she may be interested in (P2CAREER)	-0.107	**0.828**	0.014	-0.001	-0.009
How often discussed preparing for college entrance exams (P2CLGEXM)	0.094	**0.765**	-0.015	-0.009	0.091
How often discussed applying to college/other schools after high school (P2CLGAPP)	0.061	**0.789**	-0.037	0.016	0.014
Has arranged for student to attend college tour or campus program (P2CLGTOUR)	0.292	0.290	0.049	-0.033	0.004
Confidence in math tests (S1MTESTS)	-0.024	-0.022	**0.875**	0.011	-0.012
Certainty in understanding math textbook (S1MTEXTBOOK)	-0.021	-0.004	**0.816**	0.054	-0.045
Certainty in mastering skills in math (S1MSKILLS)	0.003	0.002	**0.841**	0.055	-0.025

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Confidence in excelling in math assignments (S1MASSEXCL)	-0.016	0.016	**0.876**	0.026	-0.047
Confidence in science tests (S1STESTS)	-0.021	-0.014	-0.002	**0.851**	0.009
Certainty in understanding science textbook (S1STEXTBOOK)	0.009	-0.002	0.062	**0.795**	-0.020
Certainty in mastering skills in science (S1SSKILLS)	0.035	0.020	0.081	**0.819**	-0.044
Confidence in excelling science assignments (S1SASSEXCL)	0.025	-0.008	0.053	**0.826**	-0.050
Scale of student's interest in math (in 9th grade) (X1MTHINT)	-0.085	0.019	0.676	-0.090	0.092
Scale of student's interest in science (in 9th grade) (X1SCIINT)	-0.098	0.037	-0.139	0.691	0.085
GPA in all STEM courses (X3TGPASTEM)	0.217	-0.009	0.112	-0.008	**0.559**
Credits earned in math courses (X3TCREDMAT)	-0.178	0.063	-0.062	-0.112	**0.790**
Credits earned in science courses (X3CREDSCI)	-0.013	-0.006	-0.093	0.014	**0.800**
Percent of variance explained by the factor	*2.85*	*2.85*	*4.28*	*4.08*	*2.90*

Socioeconomic Status

The results from the EFA suggest that the items appraising SES, Parental Involvement, and STEM Readiness grouped together in a manner consistent with my proposed conceptual model. The items for family income (X1FAMINCOME), mother's education (X1MOMEDU), and father's education (X1DADEDU) had factor loadings of 0.782, 0.796, and 0.821 respectively. Such high loadings suggest that most of the variance observed in these three items is accounted for by the latent construct of socioeconomic status (SES). In turn, the SES factor accounted for about 2.85% of the variance.

Parental Involvement

The parental involvement factor accounted for 2.85% of the variance. In contrast to my hypothesis, only four out of the five items I selected for parental involvement loaded in the corresponding factor. Discussing careers potentially interested in (P2CAREER), applying for college (P2CLGAPP), preparing for college admission tests (P2CLGEXM), and courses or programs at school (P2COURSE) had strong factor loadings of 0.828, 0.789, 0.765, and 0.752 respectively in the factor. Having arranged to attend college tours or campus programs (P2CLGTOUR) had a loading of 0.290 suggesting that this item is a poor indicator of the factor. Following recommendations in the literature (Brown, 2015), I removed P2CLGTOUR from further analyses.

STEM Self-Efficacy

I hypothesized that the measures I selected for self-efficacy in both math- and science-based content would reflect a single construct of STEM Self-Efficacy. The EFA results suggest that these eight items actually appraise two separate latent factors. The

items selected for self-efficacy in math (S1MTESTS, S1MTEXTBOOK, S1MSKILLS, and S1MASSECL) had large factor loadings of 0.875, 0.816, 0.841, and 0.876 respectively. In view of the topical area and the strong loadings associated among these four items, I named the factor "Math Self-Efficacy." This factor accounts for 4.28% of the variance.

Similarly, the items selected for self-efficacy in science (S1STESTS, S1STEXTBOOK, S1SSKILLS, and S1SASSECL) had factor loadings of 0.851, 0.795, 0.819, and 0.826 respectively. This grouping within a single common factor among the set of measures suggests a latent construct specifically for self-efficacy in science. This factor accounts for 4.08% of the variance. Given these results, I proceeded with CFA, SEM, and indirect effect analyses, with separate constructs for "Math Self-Efficacy" and "Science Self-Efficacy" rather than grouping all self-efficacy variables as one construct of "STEM Self-Efficacy."

STEM Interest

I originally hypothesized that the two indicators measuring the scale of students' interest in math (X1MTHINT) and interest in science (X1SCIINT) would be grouped together into a common factor, "STEM Interest." The EFA results revealed that this was not the case. Rather, these items emerged as unique measures, suggesting that these items may serve as single indicators for separately measuring interest in math and interest in science in my conceptual model. Accordingly, I treated these items as single indicators, one measuring students' interest in math and one measuring interest in science in my subsequent SEM analyses.

STEM Readiness

As hypothesized, all three items I selected to capture STEM Readiness grouped together. GPA in all STEM courses (X3TGPASTEM), credits earned in math courses (X3TCREDMAT), and credits earned in science courses (X3TCREDSCI), had factor loadings of 0.559, 0.790, and 0.80 respectively. This factor accounts for 2.90% of the variance.

Conclusions from EFA Results

The results of the EFA led me to revise my hypothesis regarding the nature and composition of the latent factors associated to my conceptual model (see Figure 4). Accordingly, my revised model posits that the STEM readiness and conceptual development process is comprised of five latent constructs (SES, Parental Involvement, Math Self-Efficacy, Science Self-Efficacy, and STEM Readiness) and four single indicators (Math Ability, Math Interest, Science Interest, and Intention to Major in STEM). I further hypothesized that SES would be apprised by family income (X1FAMINCOME), mother's education (X1MOMEDU), and father's education (X1DADEDU), while Parental Involvement would be appraised by parent-driven discussions with their students about school courses (P2COURSE), careers (P2CAREER), preparation for college entrance exams (P2CLGEXM), and applying to college (P2CLGAPP). I also hypothesized that STEM Readiness could be reliably measured by credits earned in math (X3TCREDMAT), credits earned in science (X3TCREDSCI), and GPA in all STEM courses (X3TGPASTEM).

In alignment with the EFA results, my revised measurement model views self-efficacy as comprised of two distinct but interrelated factors: namely, Math Self-Efficacy

and Science Self-Efficacy. Moreover, I hypothesized that the construct Math-Self

Efficacy could be reliably appraised by confidence in excelling in math tests

(S1MTESTS), certainty in understanding math textbooks (S1MTEXTBOOK), certainty

in mastering math skills (S1MSKILLS), and confidence in excelling in math assignments

(S1MASSEXCL), while confidence in excelling in science tests (S1STESTS), certainty

in understanding science textbooks (S1STEXTBOOK), certainty in mastering science

skills (S1SSKILLS), and confidence in excelling in science assignments (S1SASSEXCL)

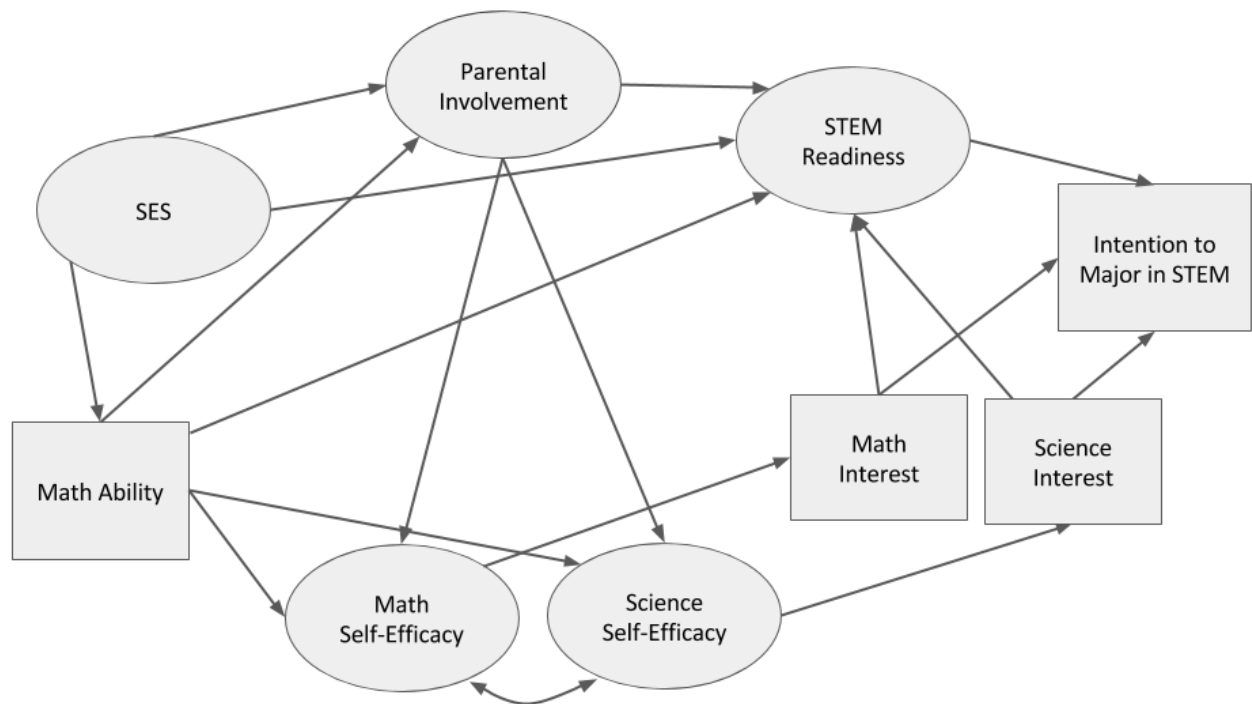would significantly load in the construct Science Self-Efficacy.

Figure 4: The STEM Readiness and Intention Development Conceptual Model (Revised)

Confirmatory Factor Analysis Results

Following the EFA, I conducted a CFA to test my hypothesis of the constructs

underscoring the revised version of the SRID Conceptual Model (Figure 4). As explained

in Chapter 3, CFA allows me to rigorously examine the extent to which the factor structure of my latent factors behave in the manner I postulated (Heck & Thomas, 2015; Brown, 2015; Wang & Wang, 2012).

The CFA results (see Table 6) indicate that the revised model is a viable representation of the data. With the exception of the chi-square test, all goodness of fit values fall within acceptable ranges (χ^2 = 1247.94, $p < 0.001$; RMSEA = 0.015, CI_{90}% = [0.014, 0.016]; CFI =0.988, TLI = 0.986). The RMSEA value of 0.015 with a 90% confidence interval from 0.014-0.016 suggests a strong model fit (Brown, 2015; Byrne, 2013; Hu & Bentler, 1999). The CFI value of 0.988 and the TLI value of 0.986, which are well above the recommended threshold of 0.95, support the hypothesized measurement component of my conceptual model (Brown, 2015). It is not surprising that the chi-square test lends no support for the five-factor model. The chi-square value is likely to yield non-supportive results with the presence of large sample sizes, as is the case in this study (Brown, 2015).

Table 6 displays the CFA results. All loadings are reported in standardized units. The 18 items in the analysis displayed loadings in their corresponding factor far exceeding the recommended value of 0.50 (Brown, 2015) (see Table 6). Furthermore, all latent factors were well appraised by their corresponding items. The reliability of the latent factors, as appraised by Raykov's (2009) method of composite reliability, ranged from 0.733 to 0.942, above the recommended threshold of 0.7 (Hair, Black, Babin, & Anderson, 2010; Hancock & Mueller, 2001).

Table 6: Measurement Component Results (Standardized)

Measure	Socioeconomic Status	Parental Involvement	Math Self-Efficacy	Science Self-Efficacy	STEM Readiness
			Construct		
X1FAMINCOME	0.717	-	-	-	-
X1MOMEDU	0.774	-	-	-	-
X1DADEDU	0.810	-	-	-	-
P2COURSE	-	0.693	-	-	-
P2CAREER	-	0.781	-	-	-
P2CLGEXM	-	0.882	-	-	-
P2CLGAPP	-	0.836	-	-	-
S1MTESTS	-	-	0.911	-	-
S1MTEXTBOOK	-	-	0.848	-	-
S1MSKILLS	-	-	0.896	-	-
S1MASSEXCL	-	-	0.928	-	-
S1STESTS	-	-	-	0.874	-
S1STEXTBOOK	-	-	-	0.833	-
S1SSKILLS	-	-	-	0.893	-
S1SASSEXCL	-	-	-	0.890	-
X3TGPASTEM	-	-	-	-	0.555
X3TCREDMAT	-	-	-	-	0.664
X3TCREDSCI	-	-	-	-	0.840
ω *Composite Reliability*	0.811	0.877	0.942	0.927	0.733
Goodness of Fit Indices	$\chi^2 = 1247.94$, $p < 0.001$ RMSEA = 0.015, $CI_{90}\%$ = 0.014, 0.016 CFI =0.988, TLI = 0.986				

Socioeconomic Status

As hypothesized, family income, mother's education, and father's education had large and significant loadings in the latent factor of SES. With a loading of 0.810, father's education was the item that most defined SES, followed by mother's education (0.774) and family income (0.717). Altogether, these three indicators constitute robust measures of the latent factor with a reliability coefficient of 0.811.

Parental Involvement

The latent factor of Parental Involvement is most represented by parent-driven discussions with students about college exams (0.882), followed by discussions of college admission tests (0.836), planning future careers (0.781), and discussion of school courses (0.693). Altogether, the four items provided a robust measure of the construct with a reliability value of 0.877.

Math Self-Efficacy

Math Self-Efficacy is most represented by students' confidence in excelling in math assignments (0.928), closely followed by confidence in excelling in math tests (0.911), certainty in mastering math skills (0.896), and certainty in understanding math textbooks (0.848). The reliability coefficient of 0.942 indicates that these four items comprise a robust measure of the latent factor of Math Self-Efficacy.

Science Self-Efficacy

Similarly, the latent factor of Science Self-Efficacy is most represented by students' confidence in excelling in science assignments (0.890), confidence in excelling in science tests (0.874), certainty in mastering science skills (0.893), and certainty in understanding science textbooks (0.833). Altogether, these items constitute a robust

measure of Science Self-Efficacy, with a reliability coefficient of 0.927.

STEM Readiness

STEM Readiness is best measured by the number of credits earned in science courses, with its loading of 0.840. The remaining two items have significant but modest loadings in this latent factor, including the number of credits earned in math courses (0.664) and GPA in all STEM courses (0.555). These more modest loadings explain why STEM Readiness displays the lowest, though entirely acceptable, reliability of 0.733 among the five latent constructs.

Conclusions from CFA Results

The results of the CFA suggest that the items I selected reliably appraise their corresponding constructs. The items selected for each of the five latent constructs, SES, Parental Involvement, Math Self-Efficacy, Science Self-Efficacy, and STEM Readiness, displayed loadings exceeding the recommended threshold.

The results also revealed moderate to strong correlations among the latent constructs (as shown in Table 7). Math Self-Efficacy and Science Self-Efficacy are one of the most highly correlated latent constructs ($r=0.47$), which is to be expected given the nature of the variables within each construct. The STEM Readiness construct is also highly correlated with SES ($r=0.48$), Parental Involvement ($r=0.43$), Math Self-Efficacy ($r=0.31$), and Science Self-Efficacy ($r=0.26$). Furthermore, Parental Involvement is correlated with SES ($r=0.46$). This significant and positive correlation among the latent factors constitutes a necessary condition in proceeding with testing the structural equation model (Byrne, 2012).

Table 7: Estimated Correlations Among Latent Constructs

	SES	Parental Involvement	Math Self-Efficacy	Science Self-Efficacy	STEM Readiness
Socioeconomic Status	1.00				
Parental Involvement	0.46	1.00			
Math Self-Efficacy	0.16	0.16	1.00		
Science Self-Efficacy	0.15	0.20	0.47	1.00	
STEM Readiness	0.48	0.43	0.32	0.26	1.00

Structural Equation Modeling Results

After documenting the measurement components of the model, I proceeded with examining the hypothesized connections among the constructs, which constitutes the basis for my research questions. Based on the EFA results, I hypothesized that Math Self-Efficacy and Science Self-Efficacy are separate but interrelated latent constructs, each of them with a direct link to interest in math and science (see Figure 4).

As discussed in Chapter 3, I conducted a sensitivity analysis to examine the extent to which the listwise default option in WLSMV produced biased estimates. I relied on MLR as the alternative estimation method, as it is well suited to handle missing values due to its full information maximum likelihood procedure (see Heck & Thomas, 2015; Shreiber, 2016). As reported in Chapter 3, estimates under WLSMV were not substantially different from those estimated under MLR. Consequently, I decided to rely on the WLSMV method given its flexibility in handling a mixture of categorical and continuous variables, as the ones present in the High School Longitudinal Study of 2009.

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Figure 5 displays the structural coefficients (in standardized units) associated with the SRID Conceptual Model. As revealed by the model fit indices, the SRID Conceptual Model is a plausible representation of the data. The CFI and TLI values (CFI=0.988, TLI=0.986) are very close to 1 (Heck & Thomas, 2015), and the RMSEA value of 0.015 is well below Hu and Bentler's (1999) recommended threshold of 0.06. Moreover, the 90% confidence interval associated with RMSEA falls in the range Byrne (2012) characterized as signifying good fit (CI90% = [0.014, 0.016]). The only exception to this trend is the chi-square value of 1247.94, which signifies a rejection of the model; however, this is a value that is expected given the large sample size of data in my study (Heck & Thomas, 2015; Brown, 2015).
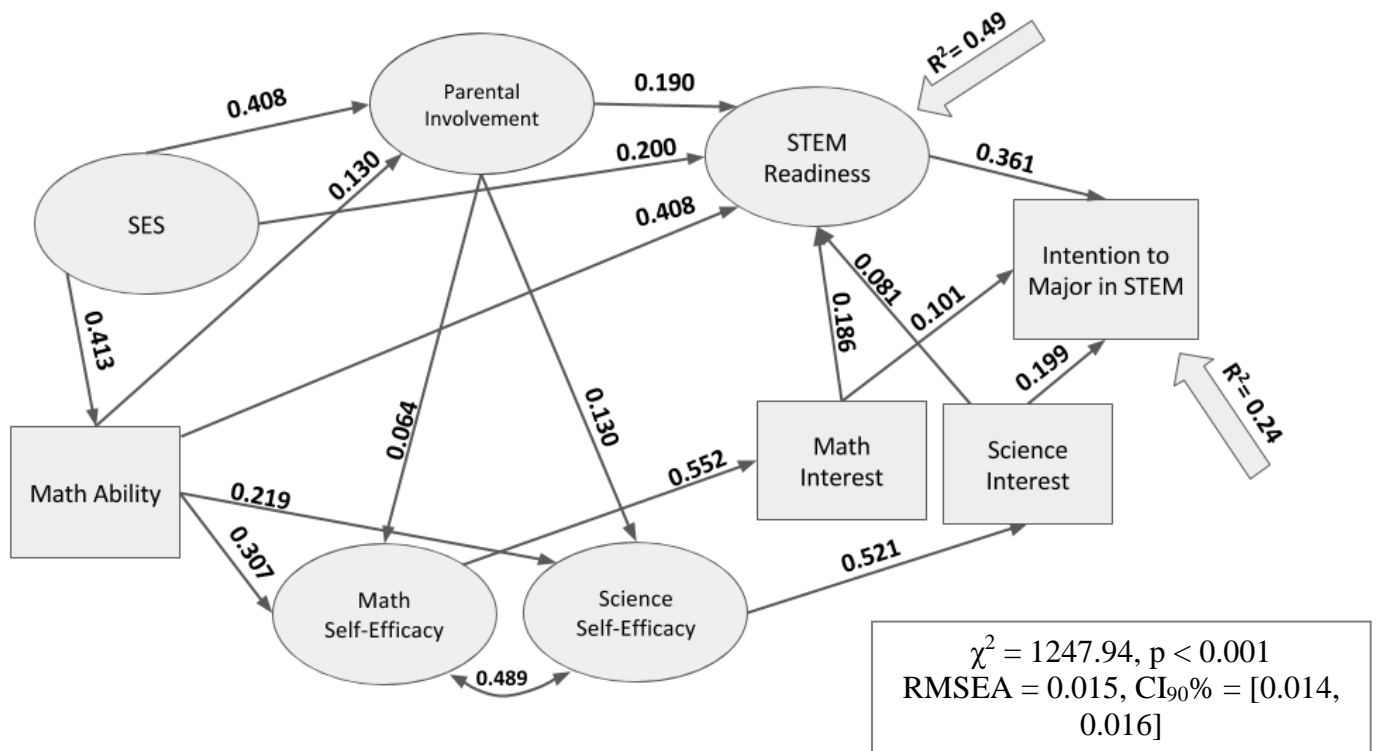

Figure 5: Structural Component Results (Standardized)

Intention to Major in STEM

The first equation examined the effects of STEM Readiness, Math Interest, and Science Interest on Intention to Major in STEM. This equation explained nearly 25% of the variance in Intention to Major in STEM (R^2=0.24). All predictors were found to exert a significant and positive effect on Intention to Major in STEM. STEM Readiness was the most important predictor, with a moderate effect size of 0.361*[28] on the outcome variable. Math Interest (0.101*) and Science Interest (0.199*) displayed small, but significant effects, on Intention to Major in STEM.

STEM Readiness

All hypothesized paths to STEM Readiness were found to be significant. Parental Involvement, SES, Math Ability, Math Interest, and Science Interest accounted altogether for about 50% of the variance in STEM Readiness (R^2=0.49). STEM Readiness was affected the most by Math Ability (0.408*), followed by SES (0.200*) and Parental Involvement (0.190*). In addition, Math Interest and Science Interest had small but significant effects on STEM Readiness (0.186*, 0.081*).

Math Interest and Science Interest

Math Interest was most affected by Math Self-Efficacy, with a significant and positive effect of 0.552*. The second strongest effect was that of Science Self-Efficacy on Science Interest, with a significant and positive effect size of 0.521*. Math Interest had a small but significant effects on STEM Readiness (0.186*) and on Intention to Major in STEM (0.101*). In addition, Science Interest had a small but significant effects

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[28] *$p<0.001$

on STEM Readiness (0.081*) and on Intention to Major in STEM (0.199*).

Math Self-Efficacy and Science Self-Efficacy

Math Self-Efficacy was most affected by Math Ability (0.307*). Parental Involvement had a small but significant effect on Math Self-Efficacy as well (0.064*). Math Self-Efficacy was affected by both Math Ability and Parental Involvement.

Similarly, Math Ability and Parental Involvement affected Science Self-Efficacy. Math Ability had a positive but relatively moderate effect size of 0.219*, while Parental Involvement had a small but significant effect on Science Self-Efficacy (0.130*). As expected, there was a correlation between Math Self-Efficacy and Science Self-Efficacy of 0.419*.

Parental Involvement

The hypothesized paths to Parental Involvement were positive and significant. Parental involvement was affected by SES, with an effect size of 0.408* and by Math Ability, with a small but significant effect of 0.130. In turn, Parental Involvement had a significant effect on STEM Readiness (0.190*).

Math Ability

As hypothesized, Math Ability was affected by SES with a significant and positive effect of 0.413*. As discussed previously, Math Ability affected Math Self-Efficacy (0.307*) and Science Self-Efficacy (0.219*), as well as affected Parental Involvement (0.130*) and STEM Readiness (0.408*).

Indirect Effects Results

As stated previously, the sub-research question of this study is: What is the

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indirect effect of STEM self-efficacy on the intention to major in a STEM field? To answer this question, I relied on Mplus to examine the indirect effect of STEM self-efficacy (i.e., math self-efficacy and science self-efficacy) in the structural model depicted in Figure 5. As noted in Chapter 3, Mplus allows researchers to estimate the direct, indirect, and total effects exhibited by STEM self-efficacy through STEM interest and STEM Readiness.

Though I hypothesized that STEM self-efficacy would be a single latent construct, the EFA results revealed that self-efficacy is actually made up of two separate latent constructs (i.e., Math Self-Efficacy and Science Self-Efficacy). This finding led me to reconceptualize self-efficacy as comprised by two separate but interrelated latent factors: Math Self-Efficacy and Science Self-Efficacy. Accordingly, I tested both the indirect effect of math self-efficacy and the indirect effect of science self-efficacy on the intention to major in a STEM field. The results are displayed in Table 8.

As displayed in Table 8, Math Self-Efficacy had a significant indirect effect on Intention to Major in STEM through Math Interest (0.056*) and through Math Interest and STEM Readiness (0.037*) for a total indirect effect of 0.093*. Science Self-Efficacy had a significant and slightly stronger indirect effect on Intention to Major in STEM through Science Interest (0.104*) and through Science Interest and STEM Readiness (0.015*), with a total indirect effect of 0.119*.

[Table 8 on next page]

Table 8: Indirect Effects of Self-Efficacy on Intention to Major in STEM

From Math Self-Efficacy to Intention to Major in STEM		
Indirect		
Math Self-Efficacy → Math Interest → Intention to Major	Math Self-Efficacy → Math Interest → STEM Readiness → Intention to Major	Total Indirect Effect
0.056	0.037	0.093
From Science Self-Efficacy to Intention to Major in STEM		
Indirect		
Science Self-Efficacy → Science Interest → Intention to Major	Science Self-Efficacy → Science Interest → STEM Readiness → Intention to Major	Total Indirect Effect
0.104	0.015	0.119

Chapter Summary

This chapter presented the results from the descriptive analysis, EFA, CFA, SEM analysis, and indirect effect testing. The descriptive analysis revealed that 23.2% of the 9th grade students intended to major in STEM by the time they were in 12th grade. Students who intended to major in STEM, in comparison to those who did not, had parents who were more involved, had higher levels of math ability, displayed higher self-efficacy measures, and were more interested in math and science. By the 12th grade, these students earned more credits in math and science and had a higher GPA in STEM courses, making them better prepared for STEM fields of study. In general, these findings suggest critical associations between students' intention to major in STEM and SES, math ability, parental involvement, STEM self-efficacy, STEM interest, and STEM readiness. The results from the descriptive analysis provide grounds for building upon further and more complex analyses.

The EFA identified five distinct latent factors and four single indicators among the selected items proposed in the conceptual model. In contrast to my hypothesis, the EFA revealed two separate factors among STEM self-efficacy items, suggesting that self-efficacy perceptions among 9th grade students fall into two separate but interrelated domains of math self-efficacy and science self-efficacy. Likewise, the EFA results suggest interest in STEM falls into two separate domains: math interest and science interest. These EFA findings led me to modify my original model, recognizing Math Self-Efficacy and Science Self-Efficacy as separate latent factors, and Math Interest and Science Interest as separate individual indicators.

The results from the CFA validated the relationships between the observed

measures and the latent factors hypothesized. Moreover, the composite reliability measure suggests that the items I selected are highly reliable in appraising each latent construct in the measurement model.

The structural model results support every path I hypothesized in my revised version of the SRID Conceptual Model. The structural model accounts for almost 50% of the variance in STEM Readiness and almost 25% of the variance in the Intention to Major in a STEM field. All paths are positive and significant, and are consistent with predictions based on theory and previous research. The interpretation of these findings in light of theory and the extant literature are explored in detail in the next chapter, Chapter 5.

Chapter V: Discussion and Conclusions

This chapter summarizes and discusses the findings of my study. Prior to this discussion, I offer an overview of the purpose of the study and the research questions. Next, I provide a brief overview of my revised conceptual model and its major hypothesis, while contrasting it with the theoretical framework of Social Cognitive Career Theory (SCCT) and other prominent literature (e.g., Wang, 2013). Following the discussion of findings, I address the limitations of the study. The chapter concludes with implications of these findings for both policy and practice, and highlights opportunities for future research.

Purpose of the Study

The purpose of this study was to investigate the various cognitive and contextual influences contributing to the developmental process that high school students undergo from 9th grade to 12th grade in preparing for and considering the selection of a major in a STEM field. This study sought to address gaps in previous research, such as the absence of parental involvement as a potential contextual factor, and improve upon both analytic and measurement shortcomings. Furthermore, this study sought to measure the impact that self-efficacy has on high school students' intention to major in a STEM field. As such, this study was guided by the following research question and sub research question:

- What are the cognitive and contextual factors impacting the developmental process high school students undergo in building readiness and intention toward a major in STEM fields of study?

    - What is the indirect effect of STEM self-efficacy on the intention to major

in a STEM field?

The STEM Readiness and Intention Development Conceptual Model

Theoretical Foundations

In order to answer the research question and sub research question, I posited a conceptual model seeking to understand the STEM readiness and intention development process: the STEM Readiness and Intention Development (SRID) Conceptual Model. My model was guided by the theoretical framework of SCCT (Lent et al., 1994) and integrated adaptations of Wang's (2013) conceptual model of STEM choice. SCCT has been a foundational framework in guiding studies on career interest development and career choice. SCCT emphasizes the interactions among key cognitive concepts (e.g., self-efficacy, interests, and goals), as well as personal inputs and contextual influences (e.g., background contextual factors and contextual influences proximal to choice behaviors).

Previous research (Moakler & Kim, 2014; Sax et al., 2015; Wang, 2013a; 2013b), as well as efforts led by Lent and colleagues (2003; 2008a; 2008b; 2013), have relied on SCCT to guide and develop a conceptual understanding of career development. Wang's (2013a) research, also guided by SCCT, sought to understand the STEM choice process while incorporating a construct from college readiness research. Wang advanced a conceptual model in which STEM choice is the result of a process linking self-efficacy, learning experiences, interests and goals, as well as college readiness.

Addressing Gaps in Previous Research

Through the development and testing of the SRID Conceptual Model, I sought to address gaps in prior research seeking to understand the STEM readiness and intention

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development process.[29] By conducting structural equation modeling (SEM) on longitudinal data tracking 9th grade students up to high school completion, using the High School Longitudinal Study of 2009 (HSLS:09), I was able to apply an appropriate statistical method for examining processes occurring through time. This method stands in sharp contrast with the majority of the literature, which has relied on applying regression techniques to cross-sectional data (Crisp et al., 2009; Lent et al., 2003; Moakler & Kim, 2014; Rogers & Creed, 2011; Sax et al., 2016).

My study also improves upon measures in STEM-related content by including relevant items of self-efficacy and interest in both math and science domains (Hall et al., 2011; Lent et al., 1998; Moakler & Kim, 2014; Seymour & Hewitt, 1997; Wang, 2013a). Finally, this study sought to fill an important gap in the literature (Lent et al., 1994; Moakler & Kim, 2014; Wang, 2013a) by including parental involvement as a key factor in the consideration of a STEM major. While parental involvement is relevant in explaining preparation for and intention to major in a STEM field of study (Cabrera & LaNasa, 2001; Fan & Chen, 2001; Ferry et al., 2000; Hall et al., 2001; Hill & Tyson, 2009; Jeynes, 2007), this construct had not been previously examined as an influential component in the STEM choice process (Moakler & Kim, 2014; Sax et al., 2016; Wang, 2013).

Building the Conceptual Model

Cognitive Components. Guided by the foundational framework of SCCT, my conceptual model incorporated the *cognitive components* of STEM self-efficacy and STEM interest, acknowledging the important role these factors have on STEM readiness

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[29] Chapter 2 provides a detailed overview of what is known and unknown in the research on this topic, while describing in detail the gaps in previous research.

and the intention to major in STEM (Bandura, 1994; Hackett & Betz, 1995; Lent et al., 2003; Rittmayer & Beier, 2008). Building upon Wang's (2013) study, my conceptual model incorporated the STEM-specific construct of STEM readiness. STEM readiness can also be regarded as an operationalization of SCCT's *learning experiences*, as it includes high school students' exposure to and performance in STEM-related coursework (Chen, 2013; Ferry et al., 2000; Mattern et al., 2015; Sadler et al., 2012). I also considered Intention to Major in STEM (the main outcome construct) as a cognitive component. As supported by previous research, intention to major in STEM indicates an action-oriented cognitive concept – also known as planned behavior (Ajzen, 1991) – which Wang (2013a) demonstrated has the most significant influence on actual entrance into STEM fields.

  Contextual Components. My conceptual model represented socioeconomic status (SES) as *background characteristics*, acknowledging the role that SES plays in the STEM readiness and intention development process (Cabrera & LaNasa, 2000; Eagle, 1989; Lee & Burkam, 2002; Ma, 2009; Perna, 2006). Also aligned with SCCT, my conceptual model included math ability as a *personal input* which influenced the STEM readiness and intention development process (Cabrera & LaNasa, 2000; Conley, 2007; Hackett, 1985; Rohde & Thompson, 2007). According to SCCT, *contextual influences proximal to choice behavior* are influences that are directly related to career choice concerns, and moderate the relationship of interests with choice goals (Lent et al., 1994). To address gaps in previous research, my model incorporated parental involvement as *contextual influences proximal to choice behavior* (Cabrera & LaNasa, 2001; Fan & Chen, 2001; Ferry et al., 2000; Hall et al., 2001; Hill & Tyson, 2009; Jeynes, 2007).

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Revising the Conceptual Model

Upon conducting the exploratory factor analysis (EFA), I revised the original SRID Conceptual Model. The revised version of the SRID Conceptual Model conceptualizes math and science as two separate, though interrelated, domains for the constructs of both STEM Self-Efficacy and STEM Interest.[30] Each of these constructs was defined by its own set of indicators. The revised model acknowledges these separate domains in my hypothesis of the STEM readiness and intention development process for high school students.

Testing the Conceptual Model

I relied on confirmatory factor analysis (CFA) to ascertain the extent to which the measures I selected were reliable and valid indicators of the five latent constructs embedded in the revised version of the SRID Conceptual Model. In summary, the CFA results confirmed my hypothesis that the five hypothetical constructs and their items provide a plausible representation of the data. The five constructs in the model were well-appraised, with composite reliability coefficients ranging from 0.733 to 0.942.

Having satisfied the measurement condition, I then conducted SEM to test whether the hypothesized connections among the constructs envisioned in my model held. The SEM results suggested that my model – which was developed to answer my primary research question – was a viable representation of the factors influencing the STEM readiness and intention development process among high school students (χ^2 = 1247.94, $p < 0.001$; RMSEA = 0.015, $CI_{90}\%$ = 0.014, 0.016; CFI =0.988, TLI = 0.986). The structural model explains almost 50% of the variance in STEM Readiness (R^2=0.49),

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[30] See Chapter 4: Results for a detailed description of the revisions made to the conceptual model, following the results from the EFA.

and almost 25% of the variance in the Intention to Major in STEM fields (R^2=0.24). The SEM findings suggest that SES, math ability, parental involvement, math self-efficacy, science self-efficacy, math interest, and science interest, are critical factors contributing to the process of building STEM readiness and the intention to major in STEM among high school students. The following sections discuss the results associated with each of the constructs in the SRID Conceptual Model[31].

Discussion

Socioeconomic Status

The results of the SEM analysis revealed that SES had a strong and significant effect on Math Ability (0.413*) and Parental Involvement (0.408*), while exerting a moderate effect on STEM Readiness (0.200*). These results are consistent with previous research that emphasizes the role SES plays in academic preparation and educational achievement (Cabrera & LaNasa, 2000; Lee & Burkam, 2002; Perna, 2005; Rowan-Kenyon, 2007; Sirin, 2005; White, 1982). In particular, previous research highlights the impact of SES on math ability (Lee & Burkam, 2002; Reyes & Stanic, 1988; Sirin, 2005) and parental involvement (Eagle, 1989). As previous research suggests, students with a higher SES are more likely to have a stronger math ability, as well as parents who were more involved in their schooling and educational experiences.

In addition, the results of my study are aligned with previous literature suggesting that SES plays a role in the extent to which a student becomes prepared for a STEM field

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[31] As mentioned in Chapter 3, *constructs* are designated by the capitalization of these factors, while the *concepts* are designated by non-capitalization of these factors (e.g. Parental Involvement (construct) vs. parental involvement (concept)).

of study (Cabrera & LaNasa, 2000; Hoffer, Rasinski, & Moore, 1995; Lee & Burkam, 2002; Perna, 2006). These findings are also consistent with the work of Ma (2009), whose study highlights the role that SES plays in students' selection of a college major. In summary, as predicted by both SCCT and the SRID Conceptual Model, SES is a key contextual factor in the STEM readiness and intention development process.

Math Ability

Math Ability had a strong effect on STEM Readiness (0.408*), and a moderate effect on Math Self-Efficacy (0.307*) and Science Self-Efficacy (0.219*). It also had a small, but significant effect on Parental Involvement (0.130*). These findings are also consistent with the extant literature (Conley, 2007; Hackett, 1985; Rohde & Thompson, 2007; Spinath, Spinath, Harlaar, & Plomin, 2006). In particular, the strong effect of Math Ability on STEM Readiness is aligned with previous research which suggests that math ability impacts the extent to which students meet benchmarks in becoming academically prepared for a STEM field of study (Conley, 2007; Hackett, 1985; Rohde & Thompson, 2007; Spinath et al., 2006).

Math Ability also displayed a small, but significant impact on parental involvement (0.130*). This relationship is consistent with studies by Eccles and Harold (1993) and Patel and Stevens (2010), which focused on ability as a predictor of the level of parental involvement in the educational experiences of the child.

My findings also suggest a strong relationship between math ability and self-efficacy. Such a connection between these two factors is aligned with Bandura's (1993) theoretical predictions, in which students' view of their own abilities and capabilities impacts feelings of self-efficacy, and vice versa. This finding is also consistent with other

scholars who studied math ability and self-efficacy (Bell & Kozlowski, 2002; Hackett, 1985; Pajares & Kranzler, 1995). In particular, these previous works suggest that math and science self-efficacy are particularly linked to students' math ability. In other words, students with higher math ability are more likely to demonstrate stronger levels of self-efficacy in math and science domains. Aligned with SCCT, personal inputs, such as math ability, predispose a student to engage more positively in learning experiences relevant to the application of math (Lent et al., 1994).

Parental Involvement

Parental Involvement had smaller, but significant effects on STEM Readiness (0.190*), Science Self-Efficacy (0.130*), as well as Math Self-Efficacy (0.064*). The role of parental involvement in self-efficacy and STEM readiness is consistent with the literature linking parental involvement with students' overall educational experiences and academic achievement (Alliman-Brisset, Turner, & Skovholt, 2004; Ferry, Fouad, & Smith, 2000; Hill & Tyson, 2009; Turner & Lapan, 2002). Noteworthy is the fact that the indicators I selected for parental involvement are aligned with what Hill and Tyson (2009) note as a form of *academic socialization*, in which parental discussions with students about their education and future plans cultivate cultural and social capital.

These results confirm my hypothesis regarding the importance of considering parental involvement as a contextual influence proximal to choice behavior, which adds a critical dimension to the SCCT framework and the conceptual model developed by Wang (2013). The positive effect of parental involvement on STEM readiness also highlights a direct connection between contextual influences proximal to choice behavior and learning experiences, an important aspect that is not covered in the SCCT framework nor Wang's

conceptual model. In addition, the role that parental involvement has in this developmental process confirms Hall and associates' (2011) previous work, which suggests that parental influences may be among the top four influences on STEM career choice among high school students. These results confirm my hypothesis that incorporating parental involvement in the STEM readiness and intention development process addresses gaps in previous research (Lent et al., 1993; Moakler & Kim, 2014; Sax et al., 2016; Wang, 2013). Overall, these results contribute to expanding the understanding of the important role of parental involvement.

Math Self-Efficacy and Science Self-Efficacy

Confirming my hypothesis, I found that self-efficacy played a critical role in the STEM readiness and intention development process among high school students. These findings are aligned with the foundational work of Bandura (1994), who emphasized that self-efficacy can impact academic performance and future decision-making.[32] Other scholars have applied Bandura's self-efficacy theory in a career development context by interpreting the influence of self-efficacy on career choice behavior (Hackett & Betz, 1995; Lent et al., 2003; Rittmayer & Beier, 2008). The findings on self-efficacy are aligned with both SCCT and Wang's (2013a) conceptual model, which suggest that self-efficacy has a direct impact on interest in the career development process.

Prior to analyses, I originally hypothesized that all eight self-efficacy items would group together as a single factor, signifying a single latent construct of STEM Self-

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[32] Self-efficacy impacts students' academic performance through the acquisition of cognitive skills, attributional feedback, and goal setting. This may manifest in performance on e.g., exams, quizzes, homework assignments. Future decisions or personal goal setting can be affected by self-efficacy beliefs. Stronger self-efficacy beliefs tend to influence higher goal setting and stronger commitment in achieving those goals (Bandura, 1994).

Efficacy. In actuality, the EFA findings revealed that STEM self-efficacy among 9th grade students manifests as two independent, but interrelated, constructs in the domains of math and science. This important discovery highlights that self-efficacy among high school students can be developed in separate academic domains in the STEM readiness and intention development process, which is aligned with Bandura's (1994) conceptualization of self-efficacy in various academic domains. Each domain of self-efficacy plays an influential role in the STEM readiness and intention development process. In addition, this finding fills gaps in previous research, by including *science* self-efficacy as a separate construct in addition to math self-efficacy, as well as an additional dimension in measuring self-efficacy overall.

Math Self-Efficacy had the strongest impact on Math Interest (0.552*), followed by Science Self-Efficacy affecting Science Interest (0.521*). It is important to highlight that each domain of self-efficacy impacted the corresponding domain in interest. In other words, math self-efficacy impacted math interest, while science self-efficacy impacted science interest. This relationship between self-efficacy and interest in the specific domains of math and science adds a unique and important dimension to the SCCT framework and Wang's (2013) conceptual model, emphasizing the multidimensionality of STEM self-efficacy and the impact it can have on interest in various aspects of STEM-related content (i.e., math and science).

Math Interest and Science Interest

As was the case for STEM Self-Efficacy, the EFA step of my analyses revealed that STEM interest was manifested in two separate, but interrelated, indicators of math interest and science interest. As such, I incorporated math and science interest as separate

indicators. Each indicator was impacted by self-efficacy (in the corresponding domains of math and science) and both indicators impacted both STEM Readiness and Intention to Major in STEM. My findings in regard to math and science interest build upon the foundational work of Wang (2013a), by incorporating measures of interest in both math and science academic domains. The findings also identified a key relationship between math and science interest and STEM readiness, highlighting the impact of math and science interest on the extent to which students become academically prepared for STEM fields of study.

Though comparatively small, Math Interest had a significant effect on STEM Readiness (0.186*), followed by the effect of Science Interest on STEM Readiness (0.081*). Math Interest and Science Interest also had small, but significant effects on Intention to Major in STEM (0.101*, 0.199* respectively). The findings of my study support the framework of SCCT (Lent et al., 1994), as well as Wang's (2013) conceptual model, acknowledging that interest has a direct impact on the career development and decision-making process. In a STEM-related context, Seymour and Hewitt (1997) emphasized the important relationship between interest in math- and science-related content and a student's decision to pursue a career in a STEM field. Previous research suggests that students' interest in academic content has an impact on their academic achievement (Schiefele, Krapp, & Winteler, 1992; Singh, Granville, & Dika, 2002), as well as their course-taking plans (Lent, Brown, & Hackett, 1994; Thorndike-Christ, 1991; Updegraff; Eccles; Barber, & O'Brien, 1996), particularly in the areas of math and science (Hall et al., 2011; Seymour & Hewitt, 1997; Wang, 2013a).

STEM Readiness

STEM Readiness is one of the outcomes in my conceptual model, and is defined by the number of math and science courses taken, as well as GPA in STEM coursework (Mattern et al., 2015). Aligned with SCCT, I regard STEM Readiness as an operationalization of SCCT's construct of *learning experiences*. As hypothesized by SCCT, I found that learning experiences (STEM Readiness) are impacted by *personal inputs* (Math Ability) and *background contextual affordances* (SES). However, SCCT does not posit a direct impact of *contextual influences proximal to choice behavior* on learning experiences. My study addresses this gap, finding that Parental Involvement (a contextual influence proximal to choice behavior) had a positive and direct impact on STEM Readiness. Confirming my hypotheses, the results revealed that STEM Readiness was affected most by Math Ability (0.408*), followed by SES (0.200*) and Parental Involvement (0.190*). In addition, Math Interest and Science Interest had small, but significant effects on STEM Readiness (0.186*, 0.081* respectively).

These findings affirm suggestions in previous research about the relationship between STEM Readiness and other influential factors in high school students' intention development process (Cabrera & LaNasa, 2000; Hoffer, Rasinski, & Moore, 1995; Lee & Burkam, 2002; Perna, 2006; Sirin, 2005; White, 1982). More specifically, college access and choice literature emphasize a significant relationship between SES and academic achievement (Cabrera & LaNasa, 2000; Lee & Burkam, 2002; Perna, 2006; Sirin, 2005; White, 1982), particularly in the selection of courses in math and science (Hoffer, Rasinki, & Moore, 1995). Indeed, the results of my study suggest that students with a stronger math ability are more likely to take math and science courses. Furthermore,

students with a stronger math ability are more likely to earn a higher GPA in STEM-related courses than students with a weaker math ability (Conley, 2007). In addition, the results of my study confirm previous research linking parental involvement and the familial context to students' academic achievement and college preparation (Cabrera & LaNasa, 2000; Fan & Chen, 2001; Jeynes, 2007; Tierney & Auerbach, 2005). In particular, my results affirms the findings of Ferry et al.'s (2000) study, which found that parental encouragement had a significant effect on the number of math and science courses taken and the grades earned in those math and science courses.

Intention to Major in STEM

Students' intention to major in a STEM field is regarded in previous research as an important factor related to both entrance into and success in STEM fields of study (Mattern et al., 2015; National Science Foundation, 2014; Wang, 2013a). Wang's (2013a) study demonstrated that intention to major in STEM is the strongest predictor of enrollment in STEM majors in postsecondary education. Identifying the key factors throughout students' high school experience that influence students' intention to major in a STEM field can contribute to strengthening entrance into and future success in STEM fields of study.

Building upon the SCCT framework and Wang's model, the SRID Conceptual Model highlights the centrality of STEM readiness in the process that high school students undergo and its impact on students' intention to major in STEM. As such, I hypothesized that Intention to Major in STEM would be most affected by STEM Readiness. The results of my study confirmed my hypothesis: Intention to Major in STEM is most affected by STEM Readiness (0.361*). Intention to Major was also

affected by Math Interest (0.101*) and Science Interest (0.199*), confirming previous

research reflecting the important relationship between STEM interest and intention to

major in STEM (Hall et al., 2011; Lent et al., 1994; Sadler et al., 2012; Seymour &

Hewitt, 1997; Wang, 2013a).

Indirect Effect of STEM Self-Efficacy

The findings of my study emphasized a strong relationship between self-efficacy

and interest, which provided further support for the exploration of my sub research

question: "What is the indirect effect of STEM self-efficacy on the intention to major in a

STEM field?" As predicted, Math Interest and Science Interest mediated some of the

effect of Math Self-Efficacy and Science Self-Efficacy on Intention to Major in STEM.

Math Self-Efficacy had a total indirect effect of 0.093* and Science Self-Efficacy had a

total indirect effect of 0.119*.

Overall, these findings are aligned with the theoretical framework of SCCT (Lent

et al., 1994), which theorizes that self-efficacy strongly mediates career development

through interest, with interest as a strong predictor of career choice (Lent et al., 2001;

2003; Nauta, 2004; Nauta & Epperson, 2003; Scarf, 2013). Previous research also

suggests that the mediating effect of self-efficacy on intention to major in STEM is

especially relevant for adolescents in high school[33] (Bandura, 2006; Pajares, 2005).

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[33] During high school, adolescents are beginning a process of self-exploration, becoming aware of how their interests and values contribute to their occupational expectations and possible career choices (Bandura, 2006; Paa & McWhirter, 2000; Pajares, 2005). Adolescents and children also have highly adaptable self-efficacy beliefs, which can be altered and enhanced based on contextual strategies (Parjares, 2005).

Limitations

My study had several limitations that must be considered. First, the outcome variable I selected is merely a measure of student *intention*. While theories of planned behavior (Ajzen, 1985; 1991) suggest that intentions predict actual behavior, I must still draw assumptions regarding the extent to which students' consideration of a STEM major will lead to the actual pursuit of a STEM major upon their completion of high school. As new waves of follow-up data are released in the coming years, future research and analyses may allow for the inclusion and examination of additional outcome measures in the STEM readiness and intention development process, including selection of STEM majors and enrollment in STEM fields.[34]

Second, there are potential weaknesses regarding the use of secondary data.[35] This dissertation study was limited to the constraints of the design structure and measurement items. When selecting variables for each construct, I was limited to those variables and survey items included in the HSLS:09 survey design. Furthermore, many of the survey measures in HSLS:09 are self-reported measures from students, parents, administrators, and counselors. While these measures provide key information from the subject perspective, self-reported data have inherent risks of biases, including comprehension issues and response biases (Fan et al., 2006; Wilcox, 2005).

Third, school factors and school-level variables are not included in this study. This limits the extent to which I can draw conclusions about the influence of the school

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[34] Until the next follow-up data in the longitudinal study become available, intention to major is the best measure currently available for major selection. These data are currently being processed by the U.S. Department of Education's National Center for Education Statistics and are not yet publicly available.
[35] This includes the inability to develop specific survey questions and a lack of control in the timing of the survey distribution (Andersen, Prause, & Silver, 2011).

context in the STEM readiness and intention development process. It is also important to note that the SCCT model (Lent et al., 1994) and Wang's (2013) conceptual model did not incorporate the ways in which the school context impacted the career or major choice process, aside from noting that it is a potential contextual influence. Accordingly, my study specifically focused on student-level processes, including only student-level constructs and indicators. Doing so allows for the focused investigation into the *individual level* of the STEM readiness and intention development process among high school students. As such, school-level variables were intentionally not included in the analyses. Rather, other individual-level contextual factors, including SES (i.e., family income, mother's education, and father's education), math ability, and parental involvement, were added to the conceptual model and analyses to incorporate the contextual influences contributing to students' developmental processes.

Finally, there are specific limitations in regards to some of the measures selected. The only measures of math interest and science interest available in the HSLS:09 database were those taken in the base year of the longitudinal survey, when students were in 9th grade. Interests can be fluid and evolving, and interests may change as students move from 9th grade to 12th grade. My study was also affected by the absence of a measure for science ability. To the best extent possible, I sought to focus on STEM-relevant content by including measures from both math and science domains. For example, the constructs for self-efficacy included Math Self-Efficacy and Science Self-Efficacy. Similarly, for the construct of interest, I included both Math Interest and Science Interest. Unfortunately, because science ability was not measured in the HSLS:09 survey, it was only possible for me to include math ability, limiting the extent

to which I could be consistent in including both domains of math and science. However, as emphasized in previous research, math ability has not only been recognized as an important factor in educational achievement and college readiness (Cabrera & LaNasa, 2000; Conley, 2007; Perna, 2005; Rohde & Thompson, 2007), but also impacts the extent to which students meet benchmarks to become academically prepared for a STEM field of study (Hackett, 1985; Rohde & Thompson, 2007; Spinath et al., 2006). As such, this lack of inclusion of science ability may be deemed a more minor limitation of the study.

Research Contributions

This dissertation contributes to the body of research on STEM pathways by examining the process high school students undergo in building readiness and intention in their pursuit of a STEM major in college. Compared to the depth of research on STEM retention and degree completion in postsecondary education (Cole & Espinoza, 2008; Crisp et al., 2009; Graham et al., 2013; Palmer et al., 2011; Watkins & Mazur, 2013), research focusing on the STEM readiness and intention development process for high school students is a newer and less explored area of research. Scholars working in this area are beginning to investigate student major choice selection, contextual impacts on the career decision-making process, and our understanding of pathways to STEM majors (Chen, 2013; Committee on STEM, 2013; Crisp, Nora, & Taggart, 2009; Lent et al., 1994; 2000; 2001; 2003; Ma, 2009; Wang, 2013b). Consequently, it is not surprising to see that the extant literature is limited in its analytic approach (e.g., reliance in regression instead of SEM), inclusion of important contextual factors (e.g., omission of parental involvement), and quality of measures used in appraising constructs (e.g., need for

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specificity in STEM-related content).

Improved Analytic Approach

Most studies on entrance into STEM fields, with the notable exception of Wang's (2013) study, have not examined the *process* involved in the decision to select a STEM career and ultimately enroll in a STEM major field of study. Instead, the majority of extant research has focused on the characteristics of students who major in a STEM field and factors relevant in their selection of a STEM major (e.g., Crisp et al., 2009; Moakler & Kim, 2014; Sax et al., 2016). In contrast to a prevailing input-output regression analysis approach, I selected SEM as the statistical analytic technique to answer my two research questions. This statistical analysis approach allowed me to examine the process of STEM readiness and intention development, and the relationships among factors influencing this process. Moreover, the use of SEM allowed me to control for measurement error, which improved the accuracy of my estimates (Heck & Thomas, 2015).

The majority of the extant research on STEM readiness and intention development (Lent et al., 2008; Moakler & Kim, 2014; Wang, 2013; Sax et al., 2016) approached the examination of this process using samples of college students majoring in STEM. Sampling college students who have already successfully made it through the STEM pipeline limits a clear understanding of the high school experience, which should be inclusive of students unable to access higher education. In turn, this dissertation study improved upon this limitation through the use of a nationally-representative sample of high school students, to focus on developing a better understanding of the experiences occurring throughout high school for all high school students.

Improved Data and Measurement

With the exception of Wang's (2013) study, the majority of previous research on entrance into STEM fields used cross-sectional data (Moakler & Kim, 2014; Sax et al., 2016). The use of cross-sectional data is not completely aligned with this study's theoretical framework of SCCT, which suggests that career development occurs as a process through time.[36] Lent et al. (2003; 2008a; 2008b) suggested in numerous studies that longitudinal data is necessary for testing of the SCCT model, calling attention to the need for more studies to adopt this recommendation. Longitudinal data accounts for behaviors and actions over a period of time. My dissertation study sought to overcome the methodological problems associated with cross-sectional data by relying on longitudinal data from HSLS:09.

My study improves upon the appraisal of key measures in the STEM readiness and intention development process. These additional measures extend beyond the work of SCCT and Wang's (2013) conceptual model, and included improvements on measures of STEM self-efficacy and STEM interest. In addition, given the importance of parental involvement and support in future decision-making and preparation during adolescence (Keller & Whiston, 2008), my conceptual model included discussion-oriented parental involvement, which cultivates social and cultural capital, influencing the STEM readiness and intention development process for high school students.

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[36] Unlike longitudinal data, which tracks students' behaviors, actions, and experiences over an extended period of time, cross-sectional data examines different cohorts of students in one segment of time (Bowen & Wiersema, 1999).

Implications for Policy, Practice, and Future Research

This dissertation draws attention to the importance of understanding the developmental process students undergo throughout high school in their preparation for and selection of a STEM major. The SRID Conceptual Model advanced in this study can be used by policymakers and practitioners to develop a deeper and more nuanced understanding of the STEM readiness and intention developmental process. This model identifies the key influences impacting this process for high school students from 9th to 12th grade. The results from testing this model suggest that SES, math ability, parental involvement, math and science self-efficacy, and math and science interest, contribute to the extent to which students develop readiness for STEM and intention to major in a STEM field of study. A foundational understanding of this developmental process through the STEM pipeline can allow for the development of policies and practices that specifically target factors which impact students throughout high school. This contribution of knowledge and the potential use of the SRID Conceptual Model has important implications for policymakers, practitioners, and future research.

Implications for Policymakers

The United States continues to strive for an increased enrollment of students in STEM fields for global competitiveness and economic growth (Committee on STEM, 2013; National Science Board, 2015). Current federal policies implemented at the K-12 and postsecondary education level follow the national prioritization of STEM education. For example, the Every Student Succeeds Act, which replaced "No Child Left Behind," has a potential funding stream specifically geared toward STEM activities and programming in school and afterschool programs (Afterschool Alliance, n.d.; U.S.

Department of Education, n.d.). More general educational funding sources, such as the 21st Century Community Leaders Centers initiative, provide federal funding exclusively to afterschool programs, which can be geared toward academic enrichment in and exposure to STEM-related content (Afterschool Alliance, n.d.). In addition, some practices at the K-12 level have been integrated into the Common Core State Standards, while other programs have adopted a STEM focus to further strengthen K-12 math and science skills (Lee, Quinn, & Valdes, 2013; National Science Board, 2016). Furthermore, given the national focus on producing STEM graduates, policymakers have invested significant resources at the postsecondary educational level to improve retention and facilitate the persistence of students in STEM fields of study (Chen, 2013; Committee on STEM, 2013; PCAST, 2012).

Despite the implementation of current policies and practices, however, our nation must produce an additional one million graduates in STEM fields (PCAST, 2012). To achieve this goal, there must be a targeted and strategic implementation of policies and intervention programs, which are guided by and based upon empirical evidence and research (PCAST, 2012). As the findings of my study suggest, these targeted strategies may include policies addressing the key cognitive and contextual factors identified in the study, namely SES, math ability, parental involvement, math and science self-efficacy, and math and science interest. Policymakers should consider prioritizing the implementation of policies and programs that involve parents in students' educational experiences, given the impact of parental involvement on the STEM readiness and intention development process. Based on the findings of this study, policymakers should propose and support programs that encourage and prepare parents to have discussions

with their students on their courses or programs at school, their future careers, their preparation for college entrance exams, and their plans to apply to college after high school.

Moreover, programs that focus on developing self-efficacy and interest in math and science may be more likely to contribute to building readiness and intention toward STEM. Some afterschool programs have been implemented to specifically focus on offering STEM programming, which contribute to the development of self-efficacy and interest in STEM fields. For example, an afterschool program called the Evoking Learning and Understanding through Investigations in the Natural Sciences (EVOLUTIONS) is geared toward high school students from 9th grade to 12th grade. Students participate in afterschool programming in science museums, where they take an active role in the learning process by engaging in hands-on workshops, activities, and projects (Afterschool Alliance, n.d.). The outcomes of such a program suggest that program participation increases students' interest in the sciences and strengthens confidence in attitudes toward math and science (Afterschool Alliance, n.d.). Policymakers should consider the impact of afterschool programs, such as EVOLUTIONS, in influencing students' development of self-efficacy and interest in math and science. Directing resources toward funding these efforts can contribute to facilitating high school students' preparation for and intention to major in STEM fields.

Implications for Practitioners

For practitioners, the findings of this study can lead to the development of strategic intervention programs and practices at the high school level, a period when students are making important decisions about and academically preparing for their

future field of study. The SRID Conceptual Model may guide administrators, teachers, and counselors in implementing best practices for facilitating high school students' navigation of the STEM readiness and intention development process. Understanding the conceptual model can encourage practitioners at the K-12 level to acknowledge the interconnected influences contributing to movement through the STEM pipeline, and identify how these pathways can be strengthened for individual students.

For example, this proposed model draws attention to the influential role that parental involvement, math and science self-efficacy, and math and science interest, may play in STEM readiness and the intention to major in STEM. Given the significant role that parental involvement can play in the STEM readiness and intention development process, practitioners should consider investment and intervention in policies, programs, and practices at the high school level that strategically involve parents or family members. This may include STEM-related programs at schools that are designed to encourage and prepare parents to have discussions with their students on their courses or programs at school, their future careers, their preparation for college entrance exams, and their plans to apply to college. Successful programs and strategies include those that adopt a framework of "mutual responsibility for family-practitioner relationships," in which both practitioners and family members take an active role in cultivating a culture of encouragement and support (Savitz-Romer & Bouffard, 2014, p. 200). For instance, UCLA's Early Academic Outreach Program provides services and opportunities for students by working together with families and schools to cultivate a college-going culture (UCLA, n.d.). Outreach from schools can be one of the strongest predictors of the extent to which parents become involved in their student's schooling, especially among

racial/ethnic minority families (Savitz-Romer & Bouffard, 2014).

While acknowledging the impact of STEM self-efficacy and STEM interest, practitioners can also focus on developing intervention programs that encourage the development of self-efficacy in math and science domains and cultivate interest and enjoyment in math and science courses. This may include practices that strengthen self-confidence in and enthusiasm about math and science. Young women and girls, in particular, display lower levels of self-efficacy than young men and boys, especially in math and science domains (Betz & Hackett, 1986). Practitioners should focus programming that targets and supports young women and girls, who have the potential to academically succeed in STEM but may internalize lower levels of self-efficacy in math or science. Lower levels of self-efficacy may deter students from considering a major in STEM. In the classroom or school context, teachers and counselors may focus on implementing strategies to develop self-efficacy in students. This may include positive reinforcement, open-ending questioning and discussions, and increasing availability outside of the classroom (Haskell, 2016).

Some educational programs (e.g., afterschool programs, camps, and workshops) have been designed to provide opportunities for students to participate in hands-on STEM-related activities, develop STEM skills, and learn about STEM fields (AAUW, 2004; Rittmayer & Beier, 2008). For example, one program invited high school girls to participate with mentors in hands-on activities and pedagogy about water quality, which increased their interest in and likelihood of later majoring in a science-related field (AAUW, 2004). While these types of programs focus on developing skillsets and knowledge in STEM, research strongly suggests that such interactive and meaningful

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experiences outside of the classroom can develop self-efficacy in STEM (Bandura, 1994; Carpi, Ronan, Falconer, & Lents, 2007; Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; Rittmayer & Beier, 2008).

In summary, as suggested by the proposed conceptual model, strategies highlighting the key contextual and cognitive influences may contribute to a greater likelihood of building STEM readiness and intention to select a STEM major. Development of best practices that address and capitalize on the various integrated influences on these outcomes may be most impactful in facilitating STEM pathways.

Future Research

Examine by gender and race. There is an evident need to focus on the recruitment of minoritized student populations (e.g., women and racial/ethnic minorities), which are currently underrepresented in many STEM fields (APS, 2015; NSF, 2015). Targeted recruitment of minoritized populations and intervention strategies have the potential to be the driving force in increasing the overall enrollment in STEM fields across the United States. Effective implementation of such targeted strategies requires a robust understanding of the process students undergo in preparing for and considering the selection of a STEM major.

Future research will examine the extent to which the SRID Conceptual Model holds for specific student populations. While this study's model was designed for a national representation of the U.S. student body of high school students, future research may investigate the STEM readiness and intention development process for underrepresented students in STEM fields, through drawing comparisons by gender and by race/ethnicity. Given the significant disparities that exist in STEM fields by gender

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and by race/ethnicity (APS, 2015; NSF, 2015), this work will be critical in understanding the experiences of underrepresented populations of students. This research may help to identify ways to address the significant gaps that exist by gender and race in STEM fields, as well as intervention strategies for overcoming these disparities while students are in the high school developmental process. Qualitative or mixed-methods research may be appropriate to explore the ways to support underrepresented students populations in their success through the STEM pipeline.

As emphasized by the National Science Board's (2016) report, a critical approach to increasing the rate of STEM graduates involves addressing the structural barriers individuals encounter in accessing and preparing for STEM fields. Future research can use the SRID Conceptual Model as a foundation for building conceptual models for specific student populations, especially those underrepresented in STEM fields, drawing implications for how to best support marginalized students. For policymakers looking to meet the national challenge of increasing the number of students who enroll in STEM programs, it is important to focus on the populations of students that face structural barriers in accessing and preparing for STEM fields. Recruiting underrepresented populations into STEM fields can be a driving force in increasing the number of STEM graduates in the nation. The support of policies and programs – specifically for underrepresented minoritized student populations – that focus on the key cognitive and contextual factors of this study is critical in achieving this national goal.

Explore beyond high school. By identifying ways to improve pathways and facilitate students' success in the STEM pipeline, future research may explore the developmental process beyond the high school experience. Once the next wave of

HSLS:09 longitudinal data becomes available, future research could build upon the findings of this dissertation study to explore whether those who intended to major in STEM persisted in pursuing a STEM field of study in postsecondary education. Additional research may seek to investigate the experiences of students earlier in the academic pipeline, including middle school or elementary school students. This line of future research could explore how experiences prior to high school may impact STEM readiness and intention to major in STEM among high school students and beyond.

Improve STEM-related measures. Future research may continue to improve upon measures in STEM-related content. To address a limitation of this dissertation study, researchers developing longitudinal surveys may want to include additional measures of interest in STEM-related content, ensuring that they survey students about their interest throughout high school. As interest can be fluid and may evolve through time, it would be ideal to survey students (in a longitudinal survey, such as HSLS:09) about their interests at least once per year. Additionally, researchers may consider adding a measure of science ability that is assessed at the beginning of high school (i.e., during the time that math ability is assessed). A measure in science ability could help in examining the impact of science-related knowledge and abilities on self-efficacy in science and interest in science. Furthermore, additional measures of parental involvement in STEM-related content may be valuable in considering the specific role parents play in the STEM readiness and intention development process.

Consider school-level context. My dissertation study sought to explore the STEM readiness and intention development process at the student level, as supported by the theoretical framework of SCCT. As my study did not include school-level variables,

another line of future research may consider measures in the school context. For example, this may include the role of teachers and counselors, or the resources and support systems available at the high school. Specific measures may address the impact of teachers or counselors on the development of self-efficacy in math and science, as well as their role in the cultivation of math or science interest in a classroom context. Furthermore, research on the school-level context may want to investigate the extent to which school climate, school culture, and teacher expectations impact the STEM readiness and intention development process.

Expand facets of familial involvement. Though the HSLS:09 survey only includes surveys from students' parents, future researchers may want to include additional measures of familial involvement. In the cases in which parents are not present or involved, there may be other adults or family members, such as grandparents, aunts, uncles, or community members, who are involved in students' schooling or educational experiences. Family members or other adults who discuss topics with students, such as school courses, future careers, preparing for college entrance exams, and applying for college, may have a similar impact in the STEM readiness and intention development process to that of parents. Including additional measures of familial involvement beyond parental involvement can be more inclusive and can allow for the opportunity to expand upon various facets and impacts of familial involvement (Gonzalez, Moll, & Amanti, 2006; Mwangi, 2015; Savitz-Romer & Bouffard, 2012).

Conclusion

This dissertation investigated the cognitive and contextual influences contributing

to the developmental process that high school students undergo in preparing for and considering the selection of an academic major in a STEM field. Guided by the theoretical framework of SCCT (Lent et al., 1994) and Wang's (2013) conceptual model, I answered two research questions through the development and testing of a new conceptual model, the SRID Conceptual Model. My model addresses gaps in previous research, such as the absence of parental involvement. My research design overcame measurement and analytic shortcomings, while examining the moderating effect of self-efficacy on high school students' intention to major in a STEM field.

The methods I employed included conducting a descriptive analysis, EFA, CFA, and SEM, using the HSLS:09 longitudinal survey. The results of these analyses suggest several cognitive and contextual influences contributing to building STEM readiness and students' intention to major in STEM during high school. These influences include SES, math ability, parental involvement, math self-efficacy, science self-efficacy, math interest, and science interest.

The results of this study suggest key findings in regards to the process of STEM readiness and intention development among high school students. Parental involvement was found to be a key contextual influence in the STEM readiness and intention development process. This finding emphasizes the influential role that the familial context plays in cultivating capital in the STEM pipeline. Furthermore, this study revealed that STEM readiness is impacted directly by several factors, including SES, math ability, parental involvement, math self-efficacy, science self-efficacy, math interest, and science interest. Intention to major in STEM is directly impacted by STEM readiness, as well as high school students' interest in math and interest in science. In

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addition, I found that self-efficacy in math and science had a mediating effect through math and science interest on high school students' intention to major in STEM, emphasizing the critical impact of self-efficacy throughout the career development process (Lent et al., 1994).

This dissertation study has important implications for policymakers, practitioners, and future research. In particular, this chapter encouraged policymakers and practitioners to develop policies and practices that specifically target factors that directly or indirectly impact this process among high school students. This may include strategic intervention programs at the high school level to facilitate and better support students in pathways to STEM fields of study. Future research may seek to examine the STEM readiness and intention development process among underrepresented student populations, explore the process beyond high school, improve upon STEM-related measures, consider the school level-context, and expand facets of familial involvement. Overall, this dissertation study expands our knowledge of the process that leads high school students to become prepared for and aspire to pursue majors in STEM. Through facilitating this process among all student populations, we may improve overall enrollment and persistence through the STEM pipeline and contribute to the national goal of increasing the number of graduates in STEM fields of study.

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